Board of Governors of the Federal Reserve System
Washington, DC 20551

Supervisory Stress Test Model Documentation

Credit Risk Models

October 2025

This document summarizes the credit risk models that the Board of Governors of the Federal Reserve System (Board) intends to use in the 2026 Supervisory Stress Test. The following sections provide an overview of the Corporate, Commercial Real Estate, First Lien Mortgage, Home Equity, Credit Card, Auto, and Other Retail Models. Each section includes a summary of the model, model components, and alternatives considered, along with other model-specific details. Documentation on the other models that the Board intends to use in the 2026 Supervisory Stress Test is available at the following link: https://www.federalreserve.gov/supervisionreg/dfa-stress-tests-2026.htm.

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A. Corporate Model

i. Statement of Purpose

The Board uses the Corporate Loss model ("Corporate Model") to estimate losses on corporate loans and leases that are graded using firms' corporate loan rating processes and measured at amortized cost. Except where explicitly noted, the Corporate Model projects losses using an expected-loss framework.[1] The dollar loss amounts projected by the Corporate Model are aggregated by firm and loan type for each scenario. Losses projected by the Corporate Model are a component of overall stressed losses in the stress test framework. These losses flow into net income through the provisions for loan and lease losses, which are calculated by the Provisions Model.[2]

The Board uses the Corporate Model to project quarterly losses for a variety of loan types as illustrated in Table A1. Loan-level inputs are sourced from FR Y-14Q, Schedule H.1 (Corporate) to ensure adequate granularity when assessing risk and projecting losses. Granular losses are aggregated into portfolio-level loss rates. Portfolio loss rates are then multiplied by aggregate portfolio balances from FR Y-14Q, Schedule M (Balances) to calculate total dollar amounts of corporate loan and lease losses. Loss results from different models are combined for disclosure purposes. Both Schedule H.1 and Schedule M use definitions from FR Y-9C, Schedule HC-C (Loans and Lease Financing Receivables) to determine their samples and define regulatory reporting items. Table A1 also provides the corresponding Schedule H.1 and Schedule M line items as well as how corporate loan type maps to the disclosure categories.

[1] The Corporate Model generates losses intended to address the credit risk of loans measured at amortized cost. Whole and syndicated loans that are measured on a fair value-basis are excluded. The Corporate Model only projects default risk; changes in market conditions that impact valuation, but not default, are out of scope.
[2] *See* Section B in the Aggregation Models Documentation (Provisions Model).

Table A1 - Loan Portfolios Covered by the Corporate Model

Disclosure Category	**Loan Type**	**FR Y-14Q, Schedule H.1 (Corporate) Line Reported on FR Y-9C (Loans and Lease Financing Receivables)**	**FR Y-14Q, Schedule M (Balances) Line Item[3]**
Commercial and industrial (C&I)	Commercial and industrial loans	4. Commercial and industrial loans to U.S. addresses (Schedule HC-C, item 4.a); and 5. Commercial and industrial loans to non-U.S. addresses (Schedule HC-C, item 4.b)	2.a (columns A and C), Graded[4] C&I loans
Commercial real estate (CRE), domestic	Domestic owner-occupied CRE loans	10. Loans secured by owner-occupied nonfarm nonresidential properties originated in domestic offices (FR Y-9C, Schedule HC-C, item 1.e(1))	1.b.(3).(a) (column A), Owner-occupied nonfarm nonresidential
Other Loans	Other non-consumer loans	8. All other loans, excluding consumer loans (Schedule HC-C, item 9.b(2))	5.e (columns A and C), Other commercial loans; and
	Other leases	9. All other leases, excluding consumer leases (Schedule HC-C, item 10.b)	5.f (columns A and C), Other commercial leases
	Loans to foreign governments	6. Loans to foreign governments and official institutions (including foreign central banks) (Schedule HC-C, item 7)	5.a (columns A and C), Loans to foreign governments
	International owner-occupied CRE loans	11. Loans secured by owner-occupied nonfarm nonresidential properties originated in non-domestic offices (reported within Schedule HC-C, item 1)	1.b.(3).(a) (column C), Owner-occupied nonfarm nonresidential

[3] Loans held for investment at amortized cost (HFI at AC) in domestic offices are reported in the first column, Column A. Column C contains loans HFI at AC in international offices.
[4] FR Y-14Q, Schedule H.1 (Corporate) does not require firms to report information about small business loans that are scored or delinquency managed. Small business loans are covered by the Other Retail Model – *see* Section G.

Disclosure Category	**Loan Type**	**FR Y-14Q, Schedule H.1 (Corporate) Line Reported on FR Y-9C (Loans and Lease Financing Receivables)**	**FR Y-14Q, Schedule M (Balances) Line Item[3]**
	Agricultural loans	3. Loans to finance agricultural production and other loans to farmers (Schedule HC-C, item 3)	5.b (columns A and C), Agricultural loans
	Loans to financial institutions	1. Loans to U.S. banks and other U.S. depository institutions (Schedule HC-C, item 2.a); and 2. Loans to foreign banks (Schedule HC-C, item 2.b); and 7. Loans to non-depository financial institutions (Schedule HC-C, item 9.a)	5.d (columns A and C), Loans to financial institutions
	Loans for purchasing or carrying securities	Not reported	5.c (columns A and C), Securities lending
	Domestic farm loans	Not reported	1.c (column A), Secured by farmland
	International farm loans	Not reported	1.c (column C), Secured by farmland

Despite covering a variety of loan types, the Corporate Model treats loans to corporate and commercial borrowers similarly and relies on more granular loan-level characteristics to differentiate the risk of loss and the sensitivity to macroeconomic factors. For example, while domestic owner-occupied CRE loans are collateralized by real estate, they are covered by the Corporate Model because their performance is primarily driven by the operations of the business that owns and uses the property. Several loan types have risk characteristics that differ from most corporate loans and receive different treatments. For example, loans for purchasing or carrying securities and CRE loans secured by farmland receive a low, constant loss rate.

Granular data are not collected because the burden of collection outweighs the benefit of more sensitive modeling.

ii. Model Overview

The Corporate Model estimates losses using an expected loss framework. As discussed in Section III.A. of the Enhanced Transparency and Public Accountability Proposal, expected losses (EL) for facility i in quarter t of the projection horizon are calculated as:

Equation A1 – Expected Losses

$$EL_{i,t} = PD_{i,t} \cdot LGD_{i,t} \cdot EAD_i.$$

where $PD_{i,t}$ is the estimated probability of default, $LGD_{i,t}$ is the estimated loss given default, and EAD_i is the exposure at default for loan i in projection quarter t.

The expected loss framework has been applied extensively in the banking industry and by supervisory authorities to address a host of problems ranging from day-to-day risk management issues to broader systemic and strategic concerns. Examples include, but are not limited to, models that evaluate portfolio risk management, economic capital, regulatory capital, internal transfer pricing, asset valuation, stress testing, and establishing reserves. For corporate loans, research has tended to focus on PD modeling, in part because data are more readily available and because PD modeling practices tend to be the most advanced. EAD research faces particularly severe data scarcity challenges since it involves only revolving exposures in an already limited universe of corporate defaults. Alternatives to the expected loss framework, such as rating transition matrices[5] and approaches that focus on accounting-based concepts related to charge-offs and reserves, are also used.[6] As with most loan types, the Board prefers to primarily rely on

[5] A transition matrix, also known as a stochastic matrix or probability matrix, is a square matrix where each entry describes the probability of moving from one state to another in a stochastic or random process.
[6] For a survey of processes used by selected supervisory authorities for stress testing *see* Foglia, A., 2009. Stress Testing Credit Risk: A Survey of Authorities' Approaches (International Journal of Central Banking), 9-45.

an EL framework for projecting losses on corporate loans because it allows differences in portfolio composition and risk sensitivity to be identified, estimated, and projected across the PD, LGD and EAD sub-components.

Some of the first examples of modern credit risk portfolio models in the professional literature include Gupton, Finger, & Bhatia CreditMetrics (1997), KMV's PortfolioManager, and the actuarial approach employed by Credit Suisse First Boston's CreditRisk+.[7] Detailed comparisons of these approaches are provided in Crouhy, Galai, & Mark (2000); Gordy (2000); and Allen & Saunders (2003).[8] More recent work has focused explicitly on incorporating macroeconomic dynamics, as in Pesaran, Scheurmann, Bjorn-Jakob, & Weiner (2006), and cyclicality, as in Keijsers, Dirris, & Kole (2015).[9] The Bank for International Settlement has explored the use of credit risk portfolio models for macroprudential purposes.[10] Flores, Basualdo, & Sordo (2010) have evaluated the use of PD, LGD, and EAD estimates representative of the international financial system for purposes of ensuring the adequacy of individual bank reserves as well as for macroprudential purposes.[11]

The Corporate Model estimates loss at the credit facility level using three independent sub-components: PD ("Corporate PD Model"), LGD ("Corporate LGD Model"), and EAD ("Corporate EAD Model"). The Board estimates the sub-component models using historical

[7] *See* Gupton, G., Finger, C., & Bhatia, M. , CreditMetrics - Technical Document.; Credit Suisse. (1997). *Creditrisk+*. London: Credit Suisse.
[8] *See* Crouhy, M., Galai, D., & Mark, R., 2000. A Comparative Analysis of Current Credit Risk Models (Journal of Banking & Finance), 59-117; Gordy, M. (2000). A comparative anatomy of credit risk models. Journal of Banking & Finance, 119-149; Allen, L., & Saunders, A., 2003. A Survey of Cyclical Effects in Credit Risk Measurement (BIS Working Paper).
[9] *See* Pesaran, M. H., Scheurmann, T., Bjorn-Jakob, T., & Weiner, S., 2006. Macroeconomic Dynamics and Credit Risk: A Global Perspective (Journal of Money Credit and Banking), 1211-1261; Keijsers, B., Dirris, B., & Kole, E., 2015. Cyclicality in Losses on Bank Loans (Tinbergen Institute Discussion Paper), 1-62.
[10] *See* BCBS, 2012. Models and Tools (Bank for International Settlement Working Paper), 1-34.
[11] *See* Flores, J., Basualdo, T., & Sordo, A., 2010. Regulatory Use of System-wide Estimations of PD, LDG, and EAD: Financial Stability Institute (BIS).

data on corporate payment status and loan losses, loan characteristics, and economic conditions. The expected loss framework projects losses at the loan level using loan characteristics reported on Schedule H.1 and economic conditions defined in the Board's supervisory stress test scenarios. Losses are aggregated into loss rates by firm and loan type and reconciled with projected balances from the Balances Model. Final loss rates are passed into the Provisions Model, described in Section B of the Aggregation Models Documentation.

The Corporate PD Model identifies the relationship between macroeconomic risk factors and default through linear regressions of PD on the difference between yields on BBB-rated bonds and 10-year U.S. Treasury bonds (the BBB spread) and the BBB spread four quarters prior. A third-party data vendor's estimates of company-specific estimates of the likelihood of default are used as a proxy for PD ("vendor PDs"). Linear regression (specifically ordinary least squares, or OLS) is chosen for its simplicity, ease of interpretation, and widespread applicability.

The Corporate LGD Model also incorporates macroeconomic stress via the BBB spread while accounting for collateral, lien position, and loan type. The Corporate EAD model uses a constant loan equivalent (LEQ) rate to determine the portion of the unfunded commitment drawn down at default. LEQ is calibrated using data from the Shared National Credit (SNC) Program and Schedule H.1.

a. PD Model Specification

As discussed above, the Corporate PD Model identifies the relationship between macroeconomic risk factors and default through linear regressions of PD on the difference between the BBB spread and the BBB spread four quarters prior. The Corporate PD Model uses the quarterly average vendor PD by industry category and credit risk rating group from 2006–2023. The third-party data vendor assigns companies into industries, which the Board aggregates into four broad categories: “Diversified Finance,” “Insurance/Real Estate,” “Manufacturing,” and “All Other.” Similarly, public ratings are collapsed into five categories: high investment grade (“AAA–A” equivalent), low investment grade (“BBB” equivalent), substantial credit risk (“BB” equivalent), high credit risk (“B” equivalent), and highly speculative (“CCC–C” equivalent) see Table A4 for the standardized rating scale. Geographic regions, country of domicile, or other geographic factors are not differentiated for estimation or projection in keeping with the treatment outlined in Section III.B.

Grouping by aggregate industry and “B” equivalent and better rating results in 16 separate ordinary least squares (OLS) regressions of the form:

Equation A2 – Vendor PD

$$\overline{vPD}_{r,n,t} = \alpha_{r,n} + \beta_{r,n} \cdot BBB_t + \gamma_{r,n} \cdot BBB_{t-4} + \varepsilon_{r,n,t}$$

where $\overline{vPD}$ represents the quarterly average 1-year vendor PD (divided by 4) for firms rated r in industry n at time t while BBB_t and BBB_{t-4} represent the contemporaneous and four-quarter lagged BBB spread.

The Board chose to consolidate “CCC–C” equivalent rated firms (highly speculative credit quality) into a single specification due to a lack of data:

Equation A3 – Vendor PD for “CCC-C” equivalent rated firms

$$\overline{vPD}_{CCC-C,t} = \alpha_n \cdot \{Industry_n\} + \beta_{CCC-C} \cdot BBB_t + \gamma_{CCC-C} \cdot BBB_{t-4} + \varepsilon_{r,n,t}$$

where $\{Industry_n\}$ represents the set of three industry dummy variables indexed by n. The manufacturing industry dummy variable is excluded to prevent perfect multicollinearity.[12]

[12] Perfect multicollinearity describes when one independent variable can be perfectly predicted by a combination of other independent variables. In this case, manufacturing can be perfectly predicted by Diversified Finance, Insurance/Real Estate, All Other and the intercept.

Table A2 and Table A3 provide coefficient estimates and standard errors. Standard errors have been adjusted to account for both heteroskedasticity and autocorrelation.[13]

Table A2 – Corporate PD Model Coefficient Estimates ("AAA–A" to "B" Equivalent Rated Loans)

		Coefficient and Standard Error (SE)					
Industry (n)	Rating (r)	$\alpha_{r,n}$	SE	$\hat{\beta}_{r,n}$	SE	$\hat{\gamma}_{r,n}$	SE
Diversified Finance	"AAA–A"	-0.080	0.024	0.083	0.009	0.071	0.008
	"BBB"	-0.247	0.051	0.194	0.011	0.093	0.016
	"BB"	-0.342	0.065	0.364	0.023	0.093	0.012
	"B"	-0.481	0.267	0.607	0.049	0.175	0.093
Insurance/Real Estate	"AAA–A"	-0.023	0.012	0.063	0.005	0.014	0.003
	"BBB"	-0.050	0.032	0.077	0.013	0.017	0.006
	"BB"	-0.340	0.087	0.226	0.045	0.086	0.017
	"B"	-0.489	0.071	0.370	0.025	0.201	0.022
Manufacturing	"AAA–A"	-0.012	0.009	0.027	0.003	0.007	0.002
	"BBB"	-0.055	0.010	0.056	0.004	0.014	0.003
	"BB"	-0.206	0.038	0.213	0.015	0.040	0.009
	"B"	-0.139	0.155	0.510	0.034	0.062	0.031
All Other	"AAA–A"	-0.037	0.011	0.050	0.004	0.031	0.003
	"BBB"	-0.001	0.012	0.049	0.005	0.016	0.003
	"BB"	-0.087	0.027	0.171	0.011	0.035	0.009
	"B"	-0.101	0.076	0.560	0.025	0.064	0.028

Table A3 – Corporate PD Model Coefficient Estimates ("CCC–C" Equivalent Rated Loans)

	Coefficient and Standard Error (SE)					
Industry	Industry ($\hat{\alpha}_n$)	SE	$\hat{\beta}_{CCC-C}$	SE	$\hat{\gamma}_{CCC-C}$	SE
	N/A	N/A	0.569	0.169	0.050	0.138
Diversified Finance	1.248	1.056	N/A	N/A	N/A	N/A
Insurance/Real Estate	-1.572	0.444	N/A	N/A	N/A	N/A
Manufacturing	2.031	0.573	N/A	N/A	N/A	N/A
All Other	0.471	0.263	N/A	N/A	N/A	N/A

[13] Heteroskedasticity occurs when the variance of the error term ($\varepsilon_{r,n,t}$) is not constant across observations. Autocorrelation, also known as serial correlation, measures the correlation of a variable with prior values of itself.

The Board projects the default probability for corporate exposures as reported on Schedule H.1. Internal credit risk ratings are mapped to the same common aggregate rating scale used for PD estimation as well as the “D” rating to indicate the borrower has already defaulted on the loan before projection started (see Table A4). The four broad industry categories are mapped using industrial classification codes (see Table A5). For “B” equivalent and better obligor ratings, PD is projected as:

Equation A4 – Projected Corporate PD

$$\widehat{PD}_{i,t} = \hat{\alpha}_{r_i,n_i} + \hat{\beta}_{r_i,n_i} \cdot BBB_t + \hat{\gamma}_{r_i,n_i} \cdot BBB_{t-4}$$

where r_i and n_i are the mapped obligor internal risk rating and mapped primary obligor industry, respectively, for facility i using coefficients from Table A2. PDs are projected in a similar fashion for “CCC–C” equivalent rated obligors using the consolidated industry specification (Equation A3) and coefficients from Table A3.

To prevent the possibility of negative values, a lower bound is established on $\widehat{PD}_{i,t}$ at 0.25 basis points. Defaulted facilities (assigned “D” equivalent ratings and already in default before projection starts) have PD set equal to 100 percent but defaulted facilities’ expected losses are spread over the projection horizon to prevent them from immediate realization in the first projection quarter. Fronting exposures, which represent obligations to advance funds on behalf of other participant lenders, have PD set to 0 percent. These are discussed further in Section A.2 Corporate Loss Aggregation.

(1) Rationale

The model specification is designed to capture both cross-sectional and time-series variation in PD in a simple and transparent framework. Vendor PDs allow a richer understanding of PD dynamics than binary default data, aggregate default rates, or accounting-based measures such as charge-offs. The key cross-sectional input to the model is obligor internal risk rating, which is a holistic measure summarizing a wide range of hard and soft credit-relevant information. The key time-series input to the model is the BBB spread.

Vendor PDs

The Board uses company-specific estimates of the likelihood of default from a third-party data vendor as proxy for PD in the Corporate PD Model. The main advantage of using vendor PDs over alternatives is that they are available for a relatively large, cross-sectional sample of companies over a wider range of economic conditions. The universe of large corporate loans is significantly smaller than that of small business or retail credit loans, which naturally results in fewer default observations, particularly among investment-grade obligors. Using vendor PDs allows for a richer understanding of PD dynamics than binary default data (such as what is available from third-party data vendors or reported on Schedule H.1) because it is available for non-defaulted companies. The Board has used vendor PDs as a proxy for the default rate since the Supervisory Capital Assessment Program (SCAP 2009). Alternative third-party data vendors have been evaluated and were found to provide similar advantages and disadvantages; however, the alternatives did not sufficiently increase coverage or improve consistency and stability to warrant a modeling change.

The model estimation sample period is 2006–2023. While data are available prior to 2006, they are more limited in the pre-2006 period. Board analysis indicated that starting the sample period in 2006 provided the best combination of broad coverage of obligors with characteristics and behaviors similar to current corporate obligors and sufficient historical data over a range of conditions. Importantly, the vendor PD dataset covers the 2008 financial crisis period.

Charge-off data provide an alternative to vendor PDs and are available over a longer time period; however, charge-offs have several well-established limitations. Regulatory reports such as FR Y-9C, Schedule HI-B (Charge-Offs and Recoveries on Loans and Leases and Changes in Allowances for Credit Losses) collect aggregate charge-off amounts, but these cannot be easily reconciled with the granular Schedule H.1 data collected for stress testing. For example, there is no way to differentiate portfolio credit quality in aggregate corporate loan balances or charge-offs reported in Schedules HC-C and HI-B; by contrast, Schedule H.1 includes detailed facility and borrower characteristics that permit a wide variety of segmentation options. Similarly, aggregate charge-off reporting also precludes segment level or obligor-specific estimation and projection. Expected loss sub-components cannot be independently evaluated because aggregate charge-off data commingle information from multiple exposures and therefore do not allow for the observation of the default event, exposure at default, loss, recovery, and key characteristics at the loan level. Finally, charge-off is an accounting measure that changes with accounting standards and industry practice over time. Charge-off recognition typically lags default events. Further, charge-off amounts may be recognized multiple times for a single default event. Despite these limitations, the Federal Reserve has consistently used net charge-off models to benchmark corporate loss estimates because historical charge-off data cover multiple stress periods and provide helpful insight into macroeconomic relationships and the magnitude of responses.

The Board has also considered estimating PD directly via financial data provided in Schedule H.1 or from third-party data vendors. This would reduce reliance on estimates provided by firms and third-party models while potentially capturing more nuanced PD dynamics; however, there are also drawbacks to this approach. The main limitation is that financial data are not required for multiple categories of obligors for facilities covered by Schedule H.1; therefore, obligor financials are only reported for about 40 percent of facilities.[14] To incorporate company financials and create comparable ratios across industries for modeling purposes, the Board would have to make further assumptions that would inevitably increase model complexity and operational challenges. Further, Schedule H.1 data collection began after the 2008 financial crisis and does not cover a full range of economic conditions. Schedule H.1 has collected certain data points that can be used to identify default (e.g., days past due, date of non-accrual, charge-off, and obligor internal risk rating) since its inception; however, data on disposed loans (loans subject to involuntary payoff and liquidation) only began in 2016Q1. Initial efforts to estimate PD more directly did not provide an unambiguous improvement over the current approach, leading the Board to maintain the less complex model currently in use. Nonetheless, the Board continues to research and evaluate direct PD estimation.

Use of Credit Ratings to Measure Obligor Credit Quality

The Board estimates PD by aggregate credit rating category. Credit ratings provide a single summary metric of obligor credit quality. Obligor internal risk ratings from firms' internal risk rating system are reported on Schedule H.1. Credit rating agencies independently assess the creditworthiness of certain entities and make these ratings publicly available. Whether internal or public, credit ratings reflect a wide range of information about an obligor that includes quantitative data (for example, financial ratios) and qualitative elements that involve subjective judgment (for example, strength of management).

[14] Obligor financial data are excluded for obligors (i) domiciled outside of the US; (ii) with a NAICS code beginning with 52, 5312, or 551111 (i.e., Finance and Insurance, Real Estate Agents and Brokers, or Offices of Bank or Intermediate Holding Companies); (iii) that is a nonprofit organization or federal, state, or local government or related agencies; or (iv) that is a Natural Person.

Equivalent risk measures are needed for both the estimation sample and firms' loans so that model estimates can be applied to firms' loan portfolios. Choosing internal obligor ratings to measure the credit quality of firms' corporate loans necessitates choosing a risk rating equivalent for the estimation sample. Vendor PDs are available for public companies, only some of which have public ratings. The simple, direct approach taken by the Board when estimating the Corporate PD model is to restrict the estimation sample to publicly rated companies. One potential concern raised by this approach is that restricting the estimation sample to publicly rated companies may generate losses that are too low (or too high) when applied to firms' loan portfolios, which include material amount of publicly rated and non-publicly rated obligors. However, the Board's ongoing monitoring of the Corporate PD Model's performance on publicly rated and non-publicly rated obligors finds no material difference across the segments. This finding suggests that obligor internal risk ratings mapped to a common scale are effective at measuring credit quality. Alternatively, non-ratings-based risk measures for companies without public ratings could be translated into ratings equivalents. Prior versions of the model did include companies that were not publicly rated in the estimation sample by assigning vendor PD ranges to external rating categories; however, this required additional assumptions, significantly complicated the model specification, and increased operational challenges without providing a clear performance benefit. Therefore, the Board has opted to restrict the estimation sample to publicly rated companies.

Segmentation

The Corporate PD Model differentiates model specifications according to industry and rating, both of which independently and in conjunction with each other affect PD. Mechanically, segmentation of the Corporate PD Model is accomplished through separate specifications by industry and rating. Segmentation is motivated by both conceptual and practical considerations. Differentiating by rating allows loss estimates to account for credit quality differences across portfolios while maintaining consistent treatment across firms. This approach also allows for sensitivity to macroeconomic factors to vary across ratings, as sensitivity generally increases with declining credit quality. Combining more granular public ratings into an aggregate common scale addresses data scarcity issues at both the upper and lower ends of the rating spectrum while reducing the complexity of mapping obligor internal risk ratings to the common scale. The highest credit quality loans contribute less to losses due to their low PD estimates, which further alleviates concern with collapsing multiple high credit quality ratings into a single category.

The choice to segment the Corporate PD Model by industry is driven by the empirical observation that different industries display different time-series patterns of default risk. Notably, during the 2008 financial crisis, financial obligors experienced much greater default risk as measured by increased vendor PDs relative to non-financial obligors. Further, constructing well-populated portfolios using granular industry classifications across all ratings segments is not possible. Consequently, when obligors have similar sensitivities to macroeconomic conditions, combining them into a single portfolio increases the precision of estimates and simplifies the model specification.

The selection of industry segments was determined by a mix of qualitative and quantitative analysis across a wide range of sub-industries. Cluster analysis identified potential groupings, which were subjected to expert judgment for reasonableness. The most notable outcomes of this analysis related to financial sector obligors: banks and savings and loans exhibited default risk consistent with the "All Other" category and were grouped accordingly;

"Insurance and Real Estate" exhibited low default risk and were assigned to their own category; and other financial firms (termed "Diversified Finance") exhibited high default risk and were assigned to their own category.

Macro Variable Selection

The Corporate PD Model estimates PD as dependent on the macroeconomy, which it accounts for through the BBB spread as a summary metric of corporate default risk. The 4-quarter lag value is included to capture empirical dynamics whereby increases in PDs are more persistent than increases in the BBB spread. The conceptual explanation for these dynamics is that the BBB spread consists of both compensation for default risk and premia for risk and liquidity. The risk and liquidity premium components of the BBB spread return to pre-stress levels more quickly than the default risk component.

The Board has found that the use of the BBB spread delivers the most stable and consistent results across different Corporate PD model specifications and modeling approaches. Other macro factors were explored as independent variables, notably the Chicago Board Options Exchange Market Volatility Index (VIX) and various measures of interest rates. Macroeconomic variables that describe real economic activity (e.g., unemployment, GDP, and inflation) are unstable and counterintuitive when the estimation samples include the COVID-19 pandemic.[15] The VIX is a natural choice given the role of equity volatility in distance-to-default models such as the model underlying the EDF construct. However, the VIX is correlated with the BBB spread, and coefficient estimates for the VIX were usually found to be insignificant and often had counterintuitive signs. Estimated coefficients for various measures of interest rates (Prime,

[15] Certain other stress testing models exclude the COVID pandemic from the estimation sample or control for it statistically through an indicator variable. The BBB spread is a strong, standalone financial summary variable that allows the Corporate Model to include the COVID pandemic without having to control for the idiosyncratic behavior of real economic variables during the COVID pandemic.

3-month and 5-year U.S. Treasury yields) were found to generally not be significant, and, when significant, often had counterintuitive signs. This finding is generally consistent with analysis of corporate interest rate risk in reduced-form models. The BBB spread tends to erode the significance of other macroeconomic factors because it encapsulates a comprehensive summary of the market's assessment of corporate default risk that is also captured by the other factors. Interest rate coefficients tend to have counterintuitive signs due to endogeneity—the Federal Reserve generally raises rates when the economy is doing well and lowers them when it is doing poorly. Capturing interest rate risk requires a more structural approach—for example, by directly incorporating obligor interest coverage ratios.

Prior versions of the Corporate PD Model considered many alternative specifications, including first differences[16] of dependent and independent variables, more granular segmentation, a broader set of explanatory variables, and the inclusion of companies that are not publicly rated in the estimation sample.[17] While first differences can be helpful in addressing serial correlation, this approach also introduces challenges for projecting losses. For example, when starting conditions were stressed during the COVID-19 period, the prior corporate PD model produced volatile loss projections due to its dependence on PD values established for the quarter preceding the projection horizon. Conceptually, more granular segmentation and additional explanatory variables allow response behavior to be further differentiated across segments and is heightened by more diverse risk factors. In practice, loss estimates do not differ enough to justify the additional complexity. Estimating the model in levels provides more

[16] First differences capture the amount of change in a variable from period to period; they are calculated by subtracting the first prior value of a variable from itself.
[17] Prior PD models considered alternative industry groupings (e.g., "Banking," and "Trade, Transportation & Utilities"), more granular internal obligor rating mappings, and country of domicile (domestic vs. foreign). Explanatory variables have included real GDP growth, the unemployment rate, equity market indices, and the VIX.

intuitive results and improves overall stability, and the direct linkage between ratings and macro sensitivity greatly reduces the complexity of the model.

(2) Data and Adjustments

The Board applies several data cleaning and filtering techniques before calculating quarterly average vendor PDs. Some companies are missing industry codes and/or ratings. An algorithm is used to fill in missing ratings and industry values when past or future values are available. Business identifier information is used to link public ratings with company-level one-year annualized vendor PDs. Granular public ratings and industry variables are collapsed to five broad ratings categories ("AAA–A" equivalent, "BBB" equivalent, "BB" equivalent, "B" equivalent, and "CCC–C" equivalent) and four industry groups ("Diversified Finance", "Insurance/Real Estate", "Manufacturing", and "All Other"). Quarterly averages of daily one-year annualized vendor PDs are calculated by company when rating and industry are available after data cleaning. One-year annualized vendor PDs are divided by four to allow for quarterly loss projections. Finally, equal company-weighted averages are calculated for the industry and rating groups.

The Corporate PD Model is used to project PDs for loans reported in Schedule H.1. Internal obligor risk ratings are mapped to the common credit rating scale, and the industry that reflects an obligor's primary business activity is mapped to one of the four broad industry groups.

Mapping Internal Ratings

In Schedule H.1, each reporting firm provides obligor internal risk ratings as determined by their proprietary rating systems. Firms' internal ratings are standardized to the same common scale of aggregate rating categories used for vendor PDs—plus one additional category for defaulted loans—through a mapping process. Consistent with the application of the 90th percentile overall value to missing data values as described in the Stress Testing Policy Statement, loans without obligor internal ratings are assigned "B" equivalent to align with the principle of conservatism.

Table A4 - Standardized Aggregate Rating Scale

Rating Category	**Description**	
"AAA–A" equivalent	High investment grade, implying low to minimal credit risk with extremely strong to strong capacity to repay obligations despite adverse conditions.	Investment Grade
"BBB" equivalent	Low investment grade, implying moderate credit risk with adequate capacity to repay but some weaknesses (i.e., susceptible to adverse conditions).	
"BB" equivalent	Speculative credit quality, implying substantial credit risk with ongoing weaknesses, though less vulnerable near-term to adverse conditions.	Non-Investment Grade / Speculative
"B" equivalent	Speculative credit quality, implying high credit risk with current capacity to repay and vulnerable to adverse conditions.	
"CCC–C" equivalent	Highly speculative credit quality, implying very high credit risk and reliance on favorable conditions with default likely along with adverse prospects for recovery.	
"D" equivalent	Defaulted credit. This is a consistent cross-bank rating equivalent assigned if the facility in question: - is 90 or more days past due, or - is currently in non-accrual status, or - has an internal obligor risk rating that maps to "CCC–C" or "D" and the facility reports a positive cumulative net charge-off.	Default

The Federal Reserve maps internal ratings by collecting explicit mappings of internal ratings to standardized credit ratings via direct outreach to firms. The mapping process is complicated by the fact that some firms use one-dimensional credit risk ratings systems that combine default and loss risk into a single rating while other firms use two-dimensional risk rating systems that differentiate default risk from loss severity in the event of a default. Further, firms commonly incorporate elements of regulatory asset quality ratings (i.e., special mention, substandard, doubtful, and loss), which are one-dimensional, into their internal ratings systems. In 2020, FR Y-14Q, Schedule H.4 (Internal Risk Rating) was introduced to increase the efficiency and transparency of obligor internal risk ratings along with their associated descriptions, minimum PDs, and maximum PDs. The current mapping is created through a hybrid process that uses explicit rating mappings where available, qualitative and quantitative data from Schedule H.4, and subject matter expertise. A small percentage of internal ratings maps to multiple standardized ratings. In such cases, exposures are divided proportionally and treated as multiple loans. For example, if an obligor internal rating of "15" maps to both "BB" and "B" equivalent standardized ratings, all facilities rated "15" are split into two loans, with one mapped to "BB" and the other to "B." Each split loan will be assigned half the exposure of the original but will otherwise have identical characteristics.

Imposing a consistent definition of defaulted loans requires additional treatment. To ensure a consistent mapping for defaulted loans, a uniform definition of default is applied across all firms—see Table A4. In some cases, the uniform default definition overrides the initial mapping of obligor internal risk ratings. Loans are considered in default if they are 90 or more days past due, are currently in non-accrual status, or if they have an internal obligor risk rating that maps to a "CCC–C" rating equivalent and the facility has reported a charge-off. Loans with an obligor internal risk rating mapped to default that do not do not show an additional sign of distress (i.e., 90 or more days past due, non-accrual status, or a positive cumulative net charge-off amount) are re-mapped to the lowest non-default rating ("CCC–C" equivalent) to prevent potentially overly punitive losses arising from a disconnect between internal risk ratings and the common scale.

Industry Assignment

To enable segmentation by industry, the Board maps the borrower industry classifications reported by firms to aggregate industry categories. Firms report borrower-specific industry codes according to the NAICS, GICS, and SIC classification systems on Schedule H.1.[18] These different classifications are first converted to NAICS 2007 to ensure a consistent baseline. Conversions between industrial classification systems are also publicly available. Next, NAICS 2007 industries are mapped to the same four industry categories used when estimating the Corporate PD model. If industry is not reported, obligors are assigned "All Other."

Table A5 - Mapping of NAICS 2007 to Aggregate Industry Categories

Aggregate Industry	NAICS 2007 Mapping
Diversified Finance	5222 Non-depository Credit Intermediation, 5223 Activities Related to Credit Intermediation, 5231 Securities and Commodity Contracts Intermediation and Brokerage, 5232 Securities and Commodity Exchanges, 5239 Other Financial Investment Activities, and 5259 Other Investment Pools and Funds
Insurance/Real Estate	5241 Insurance Carriers, 5242 Agencies, Brokerages, and Other Insurance Related Activities, and 5251 Insurance and Employee Benefit Funds
Manufacturing	31-33 Manufacturing
All Other	11 Agriculture, Forestry, Fishing and Hunting, 21 Mining, Quarrying, and Oil and Gas Extraction, 22 Utilities, 23 Construction, 42 Wholesale Trade, 44-45 Retail Trade, 48-49 Transportation and Warehousing, 51 Information, 5221 Depository Credit Intermediation, 5211 Monetary Authorities-Central Bank, 53 Real Estate and Rental and Leasing, 54 Professional, Scientific, and Technical Services, 55 Management of Companies and Enterprises, 56 Administrative and Support and Waste Management and Remediation Services, 61 Educational Services, 62 Health Care and Social Assistance, 71 Arts, Entertainment, and Recreation, 72 Accommodation and Food Services, 81 Other Services (except Public Administration), and 92 Public Administration

[18] *See* North American Industry Classification System concordances (www.census.gov/naics), Global Industry Classification Standard (www.msci.com/our-solutions/indexes/gics) and Standard Industrial Classification Code (www.sec.gov/search-filings/standard-industrial-classification-sic-code-list).

Nonbank financial institutions (NBFIs) play an increasingly important role in financial markets and intermediation in the United States and abroad.[19] The Board has determined that NBFIs with significantly different risk characteristics may be reported under the same industrial classification codes, which could lead to imprecise loss projections if not addressed. The Board uses an algorithm that reclassifies obligors assigned finance, insurance and real estate NAICS 2007 codes into more appropriate categories based on NBFI company names sourced from regulatory and vendor sources. The primary effect is that obligors identified as NBFIs that are REITS or real estate lenders and lessors are mapped to the "Insurance and Real Estate" aggregate category while NBFI companies identified as consumer, leasing and other lenders are mapped to "Diversified Finance."

(3) Assumptions and Limitations

The main assumptions that the Board makes using vendor PDs are that (1) vendor PDs accurately represent default rates on corporate loans and (2) the historical sensitivity of vendor PDs to the macroeconomy is a good proxy for the sensitivity of default rates to economic conditions.

Obligor internal risk ratings, mapped to a common rating scale, are used as a primary risk driver in the Corporate PD Model. This approach assumes that internal risk ratings assigned by firms accurately and consistently summarize salient credit risk factors. In addition, the model assumes that sensitivity to macroeconomic factors will vary across rating categories but that ratings, and therefore sensitivities, do not change during the projection window. Ratings transition models relax the constant rating assumption by explicitly allowing ratings to change

[19] *See* https://www.newyorkfed.org/nonbank-financial-institutions.

states; however, rating changes are infrequent and lag the precipitating event. Therefore, the Board finds the timely response of vendor PDs to changes in the macroeconomic environment to represent an important advantage for stress testing purposes.

Monitoring is in place to identify rating data quality issues, detect overall shifts, and look for evidence of directional bias in internal ratings. Reporting firms remediate internal rating data quality issues through the standard FR Y-14Q resubmission process. Like other data quality issues (e.g., missing values), an overlay may be recommended if internal risk rating data quality issues are not remediated.

(4) Questions

Question A1: The Board seeks comment on estimating PD directly from obligor defaults using detailed borrower characteristics (e.g., financial ratios) instead of the Board's current use of vendor PDs.

Question A2: The Board seeks comment on alternative modeling approaches (e.g., logistic regression, hazard modeling, quantile regressions) in place of the Board's current approach of linear regression.

Question A3: The Board seeks comment on the inclusion of companies that are not publicly rated in the PD model estimation data set instead of the Board's current approach of restricting the estimation data set to publicly rated companies.

b. LGD Model Specification

The Corporate LGD Model is a regression model that incorporates macroeconomic stress through the BBB spread while accounting for key loan characteristics. The Corporate LGD Model uses data from a third-party vendor on loan recoveries to estimate conditional LGD as a function of collateral, lien position, and loan type, with the BBB spread as a stress factor. The recovery rate for loan i in the default quarter ($Recovery_{i,t=D}$) is estimated using OLS as:

Equation A5 – Defaulted Loan Recovery Rate

$$Recovery_{i,t=D} = \alpha + \beta_k \cdot \{Collateral_i\} + \delta \cdot Revolver_i + \gamma \cdot BBB_{t=D} + \varepsilon_{i,t}$$

where $\{Collateral_i\}$ represents a set of four different loan-specific categorical dummy variables indexed by k that capture the type of collateral that secures the loan as well as lien position, $Revolver_i$ is a categorical dummy variable that identifies revolving loans,[20] and $BBB_{t=D}$ represents the BBB spread contemporaneous with default. Collateral dummy variables are included for loans secured by current assets, all assets, second or third liens, and unsecured loans; the other assets dummy variable is excluded—see Table A7.

Table A6 provides coefficient estimates and standard errors. Standard errors have been adjusted to account for both heteroskedasticity and autocorrelation.

Table A6 - Corporate LGD Model Coefficient Estimates and Standard Errors

Explanatory Variable	Coefficient	Standard Error
Intercept ($\hat{\alpha}$)	0.750	0.021
Current Assets ($\hat{\beta}_1$)	0.189	0.018
All Assets ($\hat{\beta}_2$)	0.076	0.018
Unsecured ($\hat{\beta}_3$)	-0.169	0.037
Second/Third Lien ($\hat{\beta}_4$)	-0.297	0.035
Revolver ($\hat{\delta}$)	0.098	0.012
BBB ($\hat{\gamma}$)	-0.040	0.005

LGD is calculated as one minus the recovery rate. The Federal Reserve projects LGD for corporate exposures as reported on Schedule H.1 using Equation A6 and the coefficient estimates from Table A6.

[20] Revolving loans allow obligors to draw, repay, and re-draw funds within a fixed limit.

Equation A6 – Projected Corporate LGD

$$\widehat{LGD}_{i,t} = 1 - \left(\hat{\alpha} + \hat{\beta}_k \cdot \{Collateral_i\} + \hat{\delta} \cdot Revolver + \hat{\gamma} \cdot BBB_t\right)$$

To prevent the potential for negative values of $\widehat{LGD}_{i,t}$ a lower bound is set to zero. Similarly, an upper bound is of 100 percent is set to prevent losses that exceed EAD.

(1) Rationale

Researchers in both industry and academia have found LGD modeling to be complicated by the limited number of default observations and the idiosyncratic nature of bankruptcy. Stylized empirical facts related to recovery are:[21]

- recovery distributions are bimodal, and recovery variance is high, with most ultimate recoveries either being very close to zero or to unity;
- recovery is procyclical;
- collateralization and subordination status are key determinants of recovery; and
- obligor industry may influence recovery.

The Corporate LGD Model is estimated using key factors that are important for the determination of LGD while emphasizing simplicity and transparency. Collateral type, lien position, loan type and the BBB spread are the primary determinants of LGD in the Corporate LGD Model.

Early research, including early proposals related to the Advanced Approaches Capital Framework, frequently assumed that LGD was not related to economic conditions. Frye was an early exception, finding evidence of cyclical recovery rates.[22] Araten, Jacobs Jr., & Varshney (2004) also found that LGDs for unsecured loans exhibit a relatively high correlation with the

[21] *See* Altman, E., & Kalotay, E., 2014. Ultimate Recovery Mixtures (Journal of Banking & Finance), 116-129; Scheurmann, T., 2004. What Do We Know About Loss Given Default? In D. Shimko, (Credit Risk Models and Management 2nd Edition), Risk Books; Luck, S., & Santos, J., 2024; The Valuation of Collateral in Bank Lending (Journal of Financial and Quantitative Analysis), 2038-2067; Acharya, A., Bharath, S., & Srinivasan, A., 2007. Does Industry-Wide Distress Affect Defaulted Firms? Evidence from Credit Risk Recoveries (Journal of Financial Economics), 787-821.

[22] *See* Frye, J., 2000. Depressing Recoveries (Federal Reserve Bank of Chicago Policy Studies).

economic cycle.[23] Subsequent research using different estimation samples and approaches has generally confirmed and extended results that find that LGD increases during macroeconomic stress.[24] The Board chose the BBB spread as a stress factor because it synthesizes information on macroeconomic credit conditions into a single metric, which promotes simplicity and transparency.

Other factors such as obligor industry, firm-reported data on business lines, and the country in which the obligor is domiciled were considered as potential explanatory variables. Alternative specifications that directly included other macroeconomic risk factors such as equity prices (annual percent change in the Dow Jones Industrial Average), the unemployment rate, GDP, and VIX were also evaluated. The volatility of LGD motivated the Board to choose a simple specification with only essential components to avoid overfitting. For example, while including industry effects can improve model fit, the improvement is insufficient to offset the increased complexity and increases the potential for overfitting. An alternative specification by Frye & Jacobs Jr (2012).[25] that projected LGD as a non-linear function[26] of initial LGD and PDs was previously used. This LGD function provided an explicit, closed-form relationship that uses parameters that are readily available to most credit models; however, it is based on a more

[23] *See* Araten, M., Jacobs Jr., M., & Varshney, P., 2004. Measuring LGD on Commercial Loans: An 18-Year Internal Study (RMA Journal), 96-103.
[24] *See* Altman, E., Brady, B., Resti, A., & Sironi, A., 2005. The Link Between Default and Recovery Rates: Theory, Empirical Evidence, and Implications (The Journal of Business), 2203-2228; Dermine, J., & Neto de Carvalho, C., 2006. Bank Loan Losses-Given-Default: A Case Study (Journal of Banking & Finance), 59-117; Caselli, S., Gatti, S., & Querci, F., 2008. The Sensitivity of the Loss Given Default Rate to Systematic Risk: New Empirical Evidence on Bank Loans (Journal of Financial Services), 1-34; Bellotti, T., & Crook, J., 2012. Loss Given Default Models Incorporating Macroeconomic Variables for Credit Cards (International Journal of Forecasting), 171-182; Frye, J., & Jacobs Jr, M., 2012. Credit Loss and Systematic Loss Given Default (The Journal of Banking & Finance), 119-149; Leow, M., Mues, C., & Thomas, L., 2014. The Economy and Loss Given Default: Evidence From Two UK Retail Lending Data Sets (Journal of the Operational Research Society), 363-375; Konečný, T., Seidler, J., Belyaeva, A., & Belyaev, K., 2017. The Time Dimension of the Links Between Loss Given Default and the Macroeconomy (European Central Bank Working Paper Series), 1-37.
[25] *See* Frye, J. & Jacobs Jr, M., 2012. Credit Loss and Systematic Loss Given Default (The Journal of Credit Risk), 109-140.
[26] A non-linear function does not have a constant rate of change (i.e., it is not a straight line).

complex calibration and displays limited risk sensitivity. In addition, alternative models such as Tobit and fractional logistic regression were explored to account for the bimodality, but these yielded either similar results or worse performance. The Board believes that the current linear regression-based approach is more transparent, easier to interpret, simpler to maintain, and captures key risk factors while increasing sensitivity to macroeconomic stress.

(2) Data and Adjustments

The Board uses recovery data from a third-party vendor that provides broad coverage of defaulted companies across a range of macroeconomic conditions. The dataset consists of instrument-level recovery observations. The Board restricts the estimation sample to loans to avoid any mismatch between the estimation sample and firms' corporate loan portfolios. Nominal recovery values are discounted into present values at the default date using a domestic high yield total return index as the discount rate, following the methodology used by prior studies such as Acharya, Bharath, & Srinivasan (2007).[27]

Collateral dummy variables are constructed by combining granular collateral description information and used to differentiate the type of collateral that secures the loan as well as the lien position. For Schedule H.1, the dummy variables are constructed using a combination of lien position and security type. Details are provided in Table A7.

[27] *See* Acharya, A., Bharath, S., & Srinivasan, A., 2007. Does Industry-wide Distress Affect Defaulted Firms? Evidence from Credit Recoveries (Journal of Financial Economics), 787-821.

Table A7 - Aggregate Collateral Types

Corporate LGD Model		**FR Y-14Q, Schedule H.1 (Corporate)**	
Collateral Dummy	Collateral Description	Lien Position	Security Type
Current Assets	Accounts Receivable, All Current Assets, Cash, Inventory, Inventory & Acc. Receivable	1. First-Lien Senior	1. Cash & Marketable Securities 2. Accounts Receivable & Inventory
All Assets	All Assets, Guarantees, Most Assets	1. First-Lien Senior	4. Blanket Lien
Other Assets	All Non-current Assets, Capital Stock, Equipment, Intellectual Property, Oil & Gas Properties, PP&E, Real Estate	1. First-Lien Senior	0. Real Estate only 3. Fixed Assets excluding Real Estate 5. Other
Second/Third Lien	Second Lien, Third Lien	2. Second Lien 4. Contractually Subordinated	
Unsecured	Unsecured	3. Senior Unsecured	6. Unsecured

(3) Assumptions and Limitations

The primary assumptions and limitations in the Corporate LGD model relate to the relevance of the estimation data set and the model specification. The third-party vendor recovery data excludes foreign and financial sector obligors. Foreign loan recoveries could differ due to differences in bankruptcy laws and practices. For example, some jurisdictions are more creditor-friendly, offering more restructuring options and shorter workout periods. Public sources of facility-level data on international loan recoveries are not readily available. While aggregate regional figures reveal some difference between domestic and foreign recoveries, they offer a limited capacity for model-based adjustments.[28] After controlling for collateral and loan type, firm LGD estimates reported on Schedule H.1 are marginally higher on domestic loans than

[28] Global Credit Data (GCD), a non-profit, bank-owned data consortium, summarizes default and recovery data that cover diverse geographic regions. GCD reported corporate recovery rates of 67 percent for Africa & Middle East, 80 percent for Asia & Oceania, 75 percent for Europe and 70 percent for Latin America compared to 74 percent for North America (GCD *Annual observed recovery rate trends*, July 2024).

foreign loans. Additionally, financial institutions are not present in the vendor recovery data because their recoveries reflect the highly regulated conditions of the industry.

The Corporate LGD model estimation sample is restricted to loans. While this limits the estimation sample, it eliminates concerns that alternative instruments, such as bonds, will display recovery behavior that is systematically different. Loans are typically secured by collateral and exhibit higher recoveries. Banks monitor loan borrowers more actively than investors monitor bond issuers and have more flexibility in executing both loss mitigation and recovery strategies prior to and after default. Bonds are also typically junior to bank loans in priority for claims on a corporation's assets in the event of default. These differences can affect LGD estimates even after controlling for observable characteristics.

The Corporate LGD Model uses a linear specification even though the estimation data are bimodal with high variance. While linear regression is transparent, easy to interpret, and operationally less complex, it does not fully capture bimodality or permit non-linear responses to stress scenarios.

(4) Questions

Question A4: The Board seeks comment on including bonds in the Corporate LGD Model estimation data set instead of the Board's current approach using only loans.

Question A5: The Board seeks comment on modeling the bimodality of recovery rates instead of the Board's current linear Corporate LGD Model.

Question A6: The Board seeks comment on using the Frye & Jacobs Jr. model, average LGDs taken from stress periods (e.g., the 2008 financial crisis) or non-linear regression models instead of the Board's current linear regression Corporate LGD Model.[29]

[29] *See* Frye, J., & Jacobs Jr., M., 2012. Credit Loss and Systematic Loss Given Default (The Journal of Credit Risk), 109-140.

c. EAD Model Specification

The Corporate EAD Model uses a constant loan equivalent (LEQ) rate to determine the portion of an unfunded commitment drawn down at default. As noted previously, although "loan" and "facility" are often used interchangeably here, exposures are reported by firms at the facility level on Schedule H.1. Reporting is based on the option that best describes the primary credit facility type; therefore, facilities that are not explicitly reported as revolving may nonetheless contain both revolving and non-revolving extensions of credit. To ensure that the drawn portion of unfunded commitments is captured in EAD even when a loan is not explicitly reported as revolving, LEQ is applied to all facilities. LEQ is calibrated using data from the Shared National Credit (SNC) Program[30] and Schedule H.1.

For lines of credit and other revolving commitments, EAD equals the outstanding balance plus a portion of the unfunded commitment (i.e., the difference between the committed exposure and outstanding balance), which reflects the amount that is likely to be drawn down by the borrower in the event of default. EAD is projected as:

Equation A7 – Projected Corporate EAD

$$\widehat{EAD}_i = OB_{i,t=0} + LEQ * \left(CB_{i,t=0} - OB_{i,t=0}\right)$$

where $OB_{i,t=0}$ and $CB_{i,t=0}$ are the outstanding and committed balances, respectively, of facility i as of $t = 0$ reported on Schedule H.1. LEQ, or the loan equivalent draw rate, represents the calibrated drawdown rate. The Corporate EAD model applies a constant 50 percent LEQ—it does not vary with macroeconomic conditions or borrower or loan characteristics over time, like

[30] The SNC Program includes all U.S. syndicated loans that are classified as shared national credits (commitments of greater than $20 million that are held by three or more regulated participating entities). *See* https://www.federalreserve.gov/supervisionreg/snc.htm.

PD and LGD. For facilities without unfunded commitments, EAD is the outstanding balance at the start of the stress test ($\mathrm{EAD_i} = \mathrm{OB_{i,t=0}}$) because the borrower does not have the ability to make additional draws.[31] In addition, for facilities already in default at the start of the stress test exercise, the Board applies a 0 percent LEQ, reflecting the fact that the event of default has already occurred for these facilities.

The Board calibrated the amount that is likely to be drawn down using multiple approaches and data sets. The Board examined, among others, the historical drawdown experience for defaulted corporate facilities and EAD estimates as reported on Schedule H.1, as well as the historical drawdown experience for defaulted U.S. syndicated revolving lines of credit reported as part of the SNC Program. Estimating LEQ from defaulted loans ("defaulted loan LEQ") and inferring LEQ from firm-reported EAD estimates ("firms' LEQ") as reported on Schedule H.1 are complementary approaches that yield similar results. While SNC data cover a much longer historical period that includes multiple stress periods, these loans represent a relatively small and potentially less comprehensively representative subset of corporate exposures. The historical Schedule H.1 data covers a much broader range of corporate borrowers, but the estimation sample does not include a period of severe stress (e.g., the 2008 financial crisis period).

For defaulted loans, LEQ is calculated as:

Equation A8 – Defaulted Loan LEQ

$$LEQ_i = \frac{OB_{i,t=D} - OB_{i,t=D-4}}{CB_{i,t=D-4} - OB_{i,t=D-4}}$$

[31] The Federal Reserve collects information about a loan's outstanding balance in the item "Utilized Exposure Global" on FR Y-14Q, Schedule H (Corporate).

where $t = D$ is the quarter of default and $t = D - 4$ is four quarters prior to default. While it is possible to use methodologies other than LEQ and different time horizons longer or shorter than one year, LEQ calculated one year prior to default is both used extensively in the EAD literature and represents standard industry practice.[32]

Many defaulted loan LEQ values are less than 0 percent or greater than 100 percent, which is outside the desired range. The Board excludes LEQs below 0 percent and greater than 120 percent consistent with the standard data treatment used by industry and suggested by the literature.[33] Since LEQ has a natural lower bound at 0 percent and an upper bound at 100 percent, a two-limit, intercept-only Tobit model was also used to estimate average defaulted facility LEQs from both Schedule H.1 and SNC data:

Equation A9 – Average Defaulted Facility LEQs

$$LEQ_i^* = \beta' \cdot x_i + \varepsilon_i$$

$$LEQ_i = \begin{cases} U \ \ if \ LEQ_i^* \geq 100\% \\ LEQ_i \ \ if \ L < LEQ_i^* < U \\ L \ \ if \ LEQ_i^* \leq \ -100\% \end{cases}$$

where $\varepsilon_i \sim +\, iid\ N(0, \sigma^2)$ and U and L are the upper and lower limits, respectively. Using SNC data, the average LEQ was estimated to be 52 percent. The average LEQ estimate using Schedule H.1 data was slightly lower at 41 percent.

Alternatively, the reported EAD parameter estimates can be used to infer firms' LEQ (LEQ') as:

[32] For example, "Discussions with bank practitioners reveal that usage measurements at the one-year horizon are most relevant to them." from Moody's, 2019. Usage and Exposures at Default of Corporate Credit Lines: An Empirical Study (Moody's Analytics).
[33] *See* Moody's, 2019. Usage and Exposures at Default of Corporate Credit Lines: An Empirical Study (Moody's Analytics).

Equation A10 – Inferred Firm LEQ Estimates

$$EAD_{i,t} = \alpha + \beta \cdot OB_{i,t} + LEQ' \cdot \left(CB_{i,t} - OB_{i,t}\right) + \varepsilon_{i,t}.$$

In this model the LEQ' coefficient represents the proportion of the unfunded exposure that contributes to firms' estimated EAD. Variations of this linear specification of firms' EAD estimates using different data samples and assumptions produces estimates of firms' LEQ that range from 43 percent to 55 percent. Alternatives included but were not limited to: controlling for bank-specific effects; considering time horizons shorter than one year and longer than one year; restricting the estimation sample to only periods of stress or over a range of conditions; and considering firm-reported EAD estimates for non-revolving loans as an alternative to restricting the estimation sample to revolving loans.

Given limited observations of defaulted revolving corporate loans, the Board chose to set LEQ to 50 percent in accordance with the stress testing principles of simplicity and stability after reviewing the range of values produced by calibration exercises that are discussed above.

(1) Rationale

Several approaches were used to establish the LEQ estimate for corporate facilities with unfunded commitments. Data scarcity is the most significant limiting factor in Corporate EAD Model design and estimation. When estimating defaulted loan LEQ, the sample is constrained to only loans with unfunded commitments within the already limited universe of corporate defaults. Considering firms' reported EAD estimates provides an alternative that allows data from both defaulted and non-defaulted loans to be considered. However, this approach raises concerns regarding the appropriateness, for stress testing purposes, of relying on bank LEQs inferred from EADs developed for other purposes.

Prior research into corporate LEQ has found a wide range of estimates (38 percent to 70 percent) depending on the methodology and estimation sample. The Board chose a constant 50 percent LEQ estimate for simplicity and stability because internal analysis displays a relatively wide range of estimates that vary due to limited data when analyzed using multiple methodologies. The range of LEQ estimates produced by a diverse set of models and data in the literature is wider but otherwise consistent with those found in the Board's internal analysis.

Early studies that estimated LEQ for purposes of determining EAD using data obtained from individual banks found that LEQ declines as obligor credit rating deteriorates and increases with time remaining to default.[34] Firms behave strategically by drawing on credit lines as their credit quality deteriorates, and banks may not be able to reduce limits to address the increased risks they pose. Utilizing Spanish banking data, Jimenez, Lopez, & Saurina (2009) observe a one-year LEQ of around 48 percent, suggesting that EAD is consistent across different banking systems.[35] Jacobs Jr. (2008) analyzed S&P data and reported a one-year LEQ of approximately 38 percent.[36] Emery, Gates, Marshella, & Ou (2008) highlights the potential for higher drawdowns during economic downturns, estimating stressed LEQ near 70 percent.[37] Barakova & Parthasarathy (2013) found that obligor rating is one of the most important determinants of EAD and that EAD varies over the credit cycle and is highest during contractions.[38] Bacham and Yang (2019) reports LEQ values ranging between 40 percent and 60 percent.[39] Moody's

[34] *See* Araten, M., & Jacobs Jr., M., 2001. Loan Equivalents for Revolving Credit and Advised Lines (RMA Journal), 34-39.
[35] Jimenez, G., Lopez, J., & Saurina, J., 2009. EAD Calibration for Corporate Credit Lines (Journal of Risk Management in Financial Institutions), 121-129. Jiminez, G., Lopez, J., & Saurina, J., 2009. Empirical Analysis of Corporate Credit Lines (Review of Financial Studies), 5069-5098.
[36] Jacobs Jr., M., 2008, An Empirical Study of Exposure at Default.
[37] Emery, K., Gates, D., Marshella, T., & Ou, S., 2008. Migration of Debt Structures and Revolver Usage as Firms Approach Default (Moody's Investor Service).
[38] Barakova, I., & Parthasarathy, H., 2013. Modeling Corporate Exposure at Default (OCC Working Paper), https://ssrn.com/abstract=2235218.
[39] Bacham, D. and Yang, L., 2019. RiskCalcTM Small Business." Moody's, White Paper.

(2019) analysis of middle-market corporate borrowers using data pooled from multiple U.S. financial institutions found that credit line usage is a function of time to default, borrower riskiness (rating and default probability), collateral type, commitment size, loan purpose, and prior usage.[40] Moody's estimated that an average LEQ for defaulted firms of 47 percent.

(2) Data and Adjustments

Regulatory data collected as part of both the SNC examination and Schedule H.1 were independently used to calibrate LEQ. Default for Schedule H.1 data is defined according to the Corporate PD Model (see Table A4). For SNC, non-accrual status is interpreted as default.

Schedule H.1 data are collected explicitly for stress testing, which aligns with the principle of independence as discussed in the Board's Stress Testing Policy Statement.[41] However, Schedule H.1 data have limited history and were not collected during stress events such as the 2008 financial crisis. To identify defaulted loans in Schedule H.1, the Board applied the definition of default used to determine "D" equivalent rated loans from the Corporate PD Model.

The SNC estimation sample was constructed using annual data from 2003–2013, which is centered on the 2008 financial crisis. The change to nonaccrual status was used to identify default in the SNC estimation sample. The SNC dataset was modified to retain only revolving lines of credit for which the year-over-year change in committed balance from four quarters prior to the default event was less than 5 percent. This approach avoids the potential for bias that could be introduced if a loan is restructured significantly with a related reduction (or increase) in

[40] *See* Moody's, 2019. Usage and Exposures at Default of Corporate Credit Lines: An Empirical Study (Moody's Analytics).
[41] For the full statement see Board of Governors of the Federal Reserve System. Stress Testing Policy Statement. Federal Register 40 (28 Feb. 2019): 6664-6671, https://www.federalregister.gov/documents/2019/02/28/2019-03503/stress-testing-policy-statement.

committed balances prior to default, as such cases can lead to extreme LEQ values that are outside the expected LEQ range. Limiting changes in the committed balance is also consistent with the constant balance sheet assumption, which assumes that firms maintain their current level of assets over the projection horizon.

(3) Assumptions and Limitations

The corporate LEQ estimate is not sensitive to the macroeconomic scenario and does not differentiate draw behavior across loan segments. EAD research faces particularly severe data scarcity challenges since it involves only revolving exposures in an already limited universe of corporate defaults. Given limited observations of defaulted revolving corporate loans, the Board chose a 50 percent LEQ estimate in accordance with the stress testing principles of simplicity and stability after reviewing the range of values produced by calibration exercises.

The SNC estimation sample has several limitations. If a loan were to default and be partially charged off in the year prior to default, the outstanding balance at default would commingle charge-off and draw behavior. This could result in negative draws and bias LEQ estimates downward, although this is mitigated by only retaining loans that experience small changes in their committed balance.

There is no direct field in the SNC estimation sample designating default. Consequently, the change to nonaccrual status was used to identify default in the estimation sample. This measure is available for every loan in the SNC sample and indicates when the lender does not expect to receive full repayment of the principal amount according to the conditions of the original credit agreement. Non-accrual status is based on lenders' expectations regarding collectability and differs from standard default definitions that require that obligors fail to meet their obligations, which could change default from a coincident to a leading indicator. Non-accrual status may fail to capture defaulted loans that are well collateralized due to the accounting carve-out for loans that are well-secured and in the process of collection.[42]

(4) Questions

Question A7: The Board seeks comment on the Tobit model of defaulted loan and the linear regression model of firms' LEQ, as compared to the Board's current approach of using a constant 50 percent LEQ assumption that is determined by considering a range of values from multiple methodologies.

d. Loss Aggregation

The Corporate Model combines projections for the sub-component models, $\widehat{PD}_{i,t}$ (Equation A4), $\widehat{LGD}_{i,t}$ (Equation A6), and $\widehat{EAD}_{i,t}$ (Equation A7), into model-based expected loss ($\widehat{EL}_{i,t}$) using the expected loss framework (Equation A1).

Model-based expected losses are aggregated into loss rates as:

Equation A11 – Model-Based Loss Rates

$$\widehat{LR}_{p,b,t} = \frac{\sum_{i \in p, i \in b} \widehat{EL}_{i,t}}{\sum_{i \in p, i \in b} OB_{i,t}}$$

where $\widehat{LR}_{p,b,t}$ is the projected loss rate for loan type p at firm b during quarter t calculated as the sum of model-based expected losses ($\widehat{EL}_{i,t}$) divided the corresponding sum of total outstanding balances as reported on Schedule H.1 ($OB_{i,t}$). Loss rates are applied to portfolio-level outstanding Schedule M balances from the Balances Model (see Section A of Aggregation) to project balance-adjusted expected losses ($\widehat{EL}^{*}_{p,b,t}$):

[42] A nonaccrual asset may be restored to accrual status when it becomes well secured and in the process of collection.

Equation A12 – Balance-adjusted Expected Losses

$$\widehat{EL}^{*}_{p,b,t} = \widehat{LR}_{p,b,t} \cdot \widehat{OB}_{p,b,t}$$

Final expected losses flow into net income through provisions for loan and lease losses in the Provision for Credit Loss Model (see Section C of Aggregation).

(1) Data and Adjustments

Several filters and data transformations are applied to prepare the regulatory data before projection. Loans accounted for under the fair value option (FVO) and disposed loans are excluded from exposures reported on Schedule H.1. FVO loans are separately covered by the FVO Model (see Section B of Market Risk). Disposed loans are reported for tracking and modeling purposes but do not represent an ongoing credit risk. Since PD, LGD and EAD projections are needed for the same set of facilities, these exclusions are applied consistently across all Corporate Model sub-components.

(2) Assumptions and Limitations

Immaterial Portfolios

Immaterial portfolios are not required to be reported on Schedule H.1. Since facility-level characteristics are unavailable, the Corporate Model cannot be used to project losses for immaterial portfolios directly. Instead, the 50th percentile of projected balance-adjusted loss rates across firms that report a material balance is applied to each firm's immaterial balances using the relevant loan type. Immaterial portfolios are assumed to be no better or worse than reported facilities given a lack of available data. Using the median loss rate is consistent with the treatment of immaterial portfolios as distinct from insufficient data for material portfolios per the Stress Testing Policy Statement.[43]

[43] *See* Stress Testing Policy Statement.

Loans Less Than $1 Million in Committed Balance

The loan population for Schedule H.1 does not include corporate loans with under $1 million in committed balances. However, firms report at the portfolio level in Schedule M an aggregate amount for each loan type irrespective of underlying facilities' committed balance amount. The average loss rates for each corresponding firm and loan type are applied to the Schedule M aggregate amounts (Equation A12). The implication is that corporate loans below the $1 million threshold receive the average loss rate for the corresponding loan type for each specific firm (Equation A11), consistent with Stress Testing Policy Statement on the treatment of missing data.[44]

Missing Data

For loans with missing model inputs, each missing input is generally set to the 90th percentile value calculated across all loans of the equivalent type. When an input value for a categorical variable is missing, the value that best matches the 90th percentile is used. For example, corporate loans with missing ratings are assigned a "B" equivalent rating. If more than 50 percent of records within a portfolio or segment are missing a significant share of direct model inputs, the portfolio is assigned the 90th percentile of the projected balance-adjusted loss rate, calculated in a manner consistent with the 50th percentile loss rate applied to immaterial portfolios. Conservative values are used where the data deficiency is severe enough that a modeled estimate cannot be produced for the portfolio segment or portfolio, consistent with the Stress Testing Policy Statement.[45]

If the committed balance is missing but outstanding balance is reported, the committed balance is assumed to be five times the outstanding balance. This treatment approximates the

[44] *See* Stress Testing Policy Statement.
[45] *See* Stress Testing Policy Statement.

90th percentile of the ratio of committed to outstanding balances across all loans reported on Schedule H.1 (excluding those with zero utilized or committed balance) which aligns with the conservative assumption generally applied to missing values. The 90th percentile of the ratio of committed to outstanding balances has shifted over time, from around three in the early years of Schedule H.1 data collection to above five since 2021.

Defaulted Loans

Loans with "D" equivalent ratings that are already in default before projection starts are assigned PD equal to 100 percent and LEQ equal to 0 percent. To prevent defaulted loan losses from being realized immediately in the first projection quarter, their expected losses are distributed over the 9-quarter projection horizon and LGD is projected per Equation A6. An assumption of the exact timing of losses on defaulted loans (i.e., in a single, specific projection quarter) could introduce stresses inconsistent with scenario design. Spreading losses over time avoids a large spike in projected loss that could have unintended effects.

Fronting Exposures

For loss to be incurred on a fronting exposure, both the underlying obligor and the other participant lender on whose behalf the funds were advanced must default (i.e., double default). The Board cannot explicitly model the credit risk mitigation features of fronting exposures because it does not currently collect information on the credit risk of the underlying obligor. The Board sets fronting exposures' PDs equal to 0 percent but retains their outstanding balances when calculating loss rates (Equation A11) to ensure they are scaled properly when applied to aggregate portfolio balances from Schedule M (Equation A12).

Farmland

Firms subject to the stress test do not have large portfolios of loans to finance real estate secured by farmland (Schedule HC-C item 1.b)[46] and aggregate exposures have been declining over time. A uniform, conservative annualized loss rate of 1.5 percent (i.e., a constant quarterly loss rate of 37.5 basis points) is applied to real estate loans secured by farmland over the projection horizon based on analysis of historical net charge-off rates coupled with a review of firms' internal projections of stress losses for these exposures. The Board considers the use of a fixed loss rate appropriate due to the low and declining materiality of this loan type at stress test firms.

Margin Loans

A uniform, conservative annualized loss rate (25 basis points annually or 6.25 basis points quarterly) is applied to margin loans. Margin loans include loans to purchase and carry securities as well as non-purpose securities-based loans. These loans are made for commercial purposes to individuals and businesses on margin and secured by various marketable securities. The value of the securities held as collateral exceed the value of the loan. Furthermore, the value of these securities is regularly reviewed, and more collateral must be provided if values decline such that there is a risk the lender will not be made whole in the event of default. These features significantly reduce the risk of loss on margin loans. The Board does not currently collect granular data on most margin loans, motivating the use of a simple fixed loss rate. The Board established the 25 basis point annual loss estimate based on analysis of limited historical loss data and firms' internal projections of stress losses for these exposures.

[46] Real estate loans secured by farmland are separate and distinct from loans to finance agricultural production and other loans to farmers (FR Y-9C, Schedule HC-C, item 3). Agricultural loan losses are projected normally using the Corporate Loss Model.

(3) Questions

Question A8: The Board seeks comment on using conditional LGD from the start of the projection horizon for defaulted loans, as compared to the Board's current practice of projecting conditional LGD over the projection horizon.

Question A9: The Board seeks comment on distributing losses on defaulted loans over the stress period in a non-linear fashion (e.g., indexed to the path of non-defaulted loan losses), as compared to the Board's current practice of distributing them linearly.

iii. Ad-hoc Adjustments

The corporate expected loss model makes an adjustment for FDIC shared-loss agreements (SLAs). The FDIC absorbs a portion of certain losses on specific assets sold as part of the resolution of a failing institution, while the purchaser or "Assuming Institution" only absorbs the remaining losses. The percentage of losses absorbed by the FDIC varies according to the terms of the SLA. Losses on corporate loan portfolios that have SLAs are adjusted to account for the portion absorbed by the FDIC.

B. Commercial Real Estate Model

i. Statement of Purpose

The Commercial Real Estate Loss model (the "CRE Model") is used to estimate losses for commercial real estate (CRE) loans. Specifically, the CRE Model is used to project quarterly losses for loans collateralized by domestic and international non-owner-occupied multifamily or non-farm, non-residential properties (referred to as "income-producing" loans), and construction and land development (C&LD, referred to as "construction" loans), as defined by Schedule HC-

C. The CRE Model covers both domestic and international loans in these two categories but does not project losses for CRE loans accounted for under the fair value option[47] or for real estate loans secured by owner-occupied non-farm, non-residential properties.[48]

The Board estimates the CRE Model using historical data on CRE payment status and loan losses, loan characteristics, and economic conditions. The model projects these losses with an expected-loss modeling framework, using data on firm-reported loan characteristics for CRE loans with $1 million or more in committed balances from FR Y-14Q, Schedule H.2 ("Commercial Real Estate") and the economic conditions defined in the Board's supervisory stress test scenarios.[49] As detailed in Section B.ii., some of the key loan characteristics that affect projected losses include:

- The loan type (i.e., income-producing or construction),
- The property type (e.g., multifamily, retail, hotel, office, and other),
- Loan-to-value (LTV) ratio,
- Loan size, and
- Loan age and the proximity of the loan to maturity.

The output of the CRE Model comprises quarterly projections of dollar loss amounts under a given stress test scenario, aggregated by firm and Schedule HC-C portfolio. This output flows into quarterly projections for net income through provisions for loan and lease losses, which are calculated in the Provisions Model.[50] The losses projected by the CRE model for a given loan vary based on changes in the defined economic conditions over the projection horizon. As detailed in Section B.ii., those include:

- Corporate bond spreads,

[47] These types of loans are projected by the Fair Value Option Model; see Section B in the Market Risk Model Documentation (Fair Value Option Model).
[48] These types of loans are projected by the Corporate Model; see Section A.
[49] Schedule H.2 does not require firms to report information about loans with less than $1 million in overall facility committed balances.
[50] *See* Section B in the Aggregation Models Documentation (Provisions Model).

- The unemployment rate,
- House prices, and
- CRE prices.

Many firms are active participants in the CRE debt market; collectively, banks and thrifts hold the largest share of CRE mortgages at approximately 50 percent of all debt outstanding as of 2024Q1.[51] CRE lending is an important business line for many banks, including those that participate in the supervisory stress test. As of 2024Q4, CRE loan balances comprised approximately 10 percent of all loan balances for firms covered in the 2025 supervisory stress test. Accordingly, deterioration in the performance of CRE loans can significantly impact a firm's capital position.

ii. Model Overview

The CRE Model estimates losses using a loan-level expected loss framework. Under the expected loss framework, losses for each loan i in quarter t are estimated using the following equation:

Equation B1 – Loan-Level Expected Loss Framework

$$EL_{i,t} = PD_{i,t} * LGD_{i,t} * EAD_{i,t}$$

where $EL_{i,t}$ is the expected loss, $PD_{i,t}$ is the estimated probability of default, $LGD_{i,t}$ is the estimated loss given default, and $EAD_{i,t}$ is the exposure at default for loan i in projection quarter t.

[51] *See* Trepp, CRE Mortgage Maturities & Debt Outstanding Q1 2024: Commercial Mortgages Increased by $231 Billion. July 12, 2024, https://www.trepp.com/trepptalk/cre-mortgage-maturities-debt-outstanding-q1-2024; Crosignani, M., & Prazad, S., 2024. Extend-and-Pretend in the U.S. CRE Market, http://matteocrosignani.com/site/wp-content/uploads/2024/10/CRE_Zombies_Oct24.pdf.

Each of the terms in Equation B1 is estimated using independent model sub-components; these sub-components are described in further detail in Sections B.ii.a., B.ii.b., B.ii.c. A fourth model sub-component is used to project scenario values for auxiliary, CRE-specific variables used in the PD model sub-component Section B.ii.d. A fifth model sub-component aggregates the output of each of the PD, LGD, and EAD model sub-components to project losses at the firm and portfolio level (see Section B.ii.e)—generating the final output of the CRE Model that is passed to the Provisions Model.[52]

Data used to calibrate the individual CRE model sub-components consist of loan-level regulatory reporting data from Schedule H.2, loan-level data from the Commercial Mortgage-Backed Securities (CMBS) market, transaction-level data covering CRE property sales, local indicators of CRE market performance, and a zip code-to-county map used to link properties reported on Schedule H.2 to location-specific market conditions.[53]

The overall modeling approach used for the CRE model, where expected loss is expressed as a multiplicative function of PD, LGD, and EAD, is a widely used approach to estimating potential credit loss. Risk management practitioners, regulators, and academics use the expected loss framework to estimate credit loss in various contexts, including for loan loss provisioning, stress testing, underwriting decisions, and to better understand drivers of loan performance.[54] The expected loss framework is well suited to the purpose of the CRE model and

[53] *See* Section B in the Aggregation Models Description (Provisions Model).

[53] The Board acquires supplementary data from several third-party vendor sources to supplement the FR Y-14Q, Schedule H.2 data used in calibrating the CRE model sub-components.

[54] *See* Lopez, J., & Saidenburg, M., 2000. Evaluating Credit Risk Models (Journal of Banking and Finance); Altman, E., Resti, A., & Sironi, E., 2004. Default Recovery Rates in Credit Risk Modeling: A Review of the Literature and Empirical Evidence (Economic Notes by Banca Monte Dei Paschi di Siena SpA vol. 33, no. 2-2004), 183-208; Foglia, A., 2009, Stress Testing Credit Risk: A Survey of Authorities' Approaches (International Journal of Central Banking), 9-45; Bastos, J., 2010. Forecasting Bank Loans Loss-Given-Default (Journal of Banking & Finance), 2510-2517.

conforms to the principles of supervisory stress testing outlined in the Board's Stress Testing Policy Statement[55]:

- The approach allows the Board to independently develop an internal model that utilizes the loan-level regulatory reporting data required of firms, rather than relying on models or loss estimates provided by firms.
- The approach is forward-looking; it can accept various macroeconomic scenarios, is adaptable to various counterfactuals, and allows for the sub-components to be specified with a set of independent variables that limits reliance on past outcomes.
- The approach is consistent and comparable across firms. The model pools loans from all firms and does not include firm-specific fixed effects; differences in results are driven by differences in input data.
- The approach is simple; it is a straightforward application of credit risk modeling practices that minimizes operational challenges and allows for explainable results.
- The approach produces outcomes that are robust and stable. Each of the individual model sub-components is thoroughly tested and continuously monitored for changes in performance. Model outcomes are driven by underlying risk factors and macroeconomic scenarios rather than temporary fluctuations in model performance.
- The approach allows for conservative assumptions, when necessary, given the flexibility of the specifications of the individual model sub-components. That is, among a set of reasonable alternatives, conservative choices are made (all else equal). For example, if a firm provides insufficient information for the Board to produce a projected value for any of the sub-components, a synthetic loss rate based on a high percentile is assigned.

a. PD Model Sub-Component

The PD model sub-component assumes the probability that a loan defaults depends on loan characteristics and macroeconomic factors, such as the unemployment rate. The Board defines CRE loans as in default when they are 90 days past due or other factors in the data (e.g., non-accrual status or other evidence of weak credit quality when a given loan's maturity was last extended) indicate that the loans are significantly impaired.[56] The PD component projects the probability that a loan transitions from current to default status. The model assumes that the loan, once in default, does not return to current status. As described in this section, the Board

[55] *See* Stress Testing Policy Statement.
[56] The threshold of 90 days past due is a commonly used delineation of delinquent loans that are at risk of no repayment. See, e.g., FR Y-9C, Schedule HC-N, "Past Due and Nonaccrual Loans, Leases, and Other Assets."

models the probability that a loan defaults over a single quarter using a binomial logit regression model and estimates the model using data from Schedule H.2 pooled with historical loan performance data on loans securitized in commercial mortgage-backed securities (CMBS).

(1) Model Specification

The PD model sub-component projects default probabilities ($\widehat{PD}_{i,t}$) for each loan i in each quarter t. To generate the projections, the Board estimates a logistic regression (a standard modeling approach for limited dependent variables) that relates historical data on loan performance to loan characteristics, macroeconomic conditions, and other factors. The resulting coefficient estimates are then combined with information for each loan that covered firms report on Schedule H.2 as of the reporting date used for a given supervisory stress test to project PD for each loan i in each quarter t of the projection horizon.[57] Following this step, model-projected PDs are scaled upwards for income-producing loans that are approaching maturity with a debt service coverage ratio (DSCR) less than 1.2.[58] A final step assigns synthetic PDs for loans that are reported without enough information to generate a modeled projection.

Estimation of Logistic Regression Model

The logistic regression model is specified with the following functional form:

Equation B2 – Logistic Regression Model for Probability of Default

$$PD(X_{it}) = \frac{1}{1 + \exp\left(-(\beta_0 + X_{it}'\beta)\right)}$$

where X_{it} is a vector of characteristics of loan i and relevant macroeconomic variables at time t, β_0 is an intercept term, and β is a vector of coefficients corresponding to the various loan

[57] For example, the 2024Q4 reporting date is used for the 2025 supervisory stress test.

[58] As described in further detail in section B.ii.a.(2), this adjustment allows the CRE PD model sub-component to account for the effect of interest rates on the default probability of CRE loans.

characteristics included in the model. The model is estimated using historical data on loan performance from loans reported on Schedule H.2, combined with historical loan performance data from the CMBS market from a third-party data vendor.[59] Several additional variables that provide information on macroeconomic and CRE market conditions are included. These variables are sourced from the Board macroeconomic scenarios and from a third-party data vendor. Coefficient estimates ($\hat{\beta}$) are obtained through maximum likelihood estimation. A comprehensive listing of the loan characteristics used in the model (independent variables), their transformation, the dataset from which they are sourced, their coefficient estimates, and associated standard errors is provided in Table B1.

Table B1- Independent Variables and Coefficient Estimates in the CRE PD Model Sub-Component.

Variable	Transformation	Source	Estimate	Standard Error
Constant			-8.738	0.054
Age	Loan age (in quarters)	Schedule H.2 and third-party data vendor	0.081	0.003
Age Squared	Square of loan age (in quarters)	Schedule H.2 and third-party data vendor	-0.002	0.0001
Age Cubed	Cube of loan age (in quarters)	Schedule H.2 and third-party data vendor	0.00002	0.000001
FR Y-14 Income Producing	Indicator equal to 1 if the loan is a FR Y-14 income-producing loan, 0 otherwise	Schedule H.2	-0.620	0.022
FR Y-14 Construction	Indicator equal to 1 if the loan is a FR Y-14 construction loan, 0 otherwise	Schedule H.2	-0.340	0.031

[59] As discussed in Section B.ii.a.(4), CMBS data is used to supplement Schedule H.2 data with a longer time series that includes a severe economic downturn. Many of the key summary statistics of the loan-level independent variables included in the model are generally similar across Schedule H.2 and CMBS loan samples.

Variable	Transformation	Source	Estimate	Standard Error
Retail	Indicator equal to 1 if the loan is collateralized by retail property, 0 otherwise	Schedule H.2 and third-party data vendor	-0.079	0.024
Industrial	Indicator equal to 1 if the loan is collateralized by industrial property, 0 otherwise	Schedule H.2 and third-party data vendor	-0.243	0.032
Hotel	Indicator equal to 1 if the loan is collateralized by hotel property, 0 otherwise	Schedule H.2 and third-party data vendor	-1.069	0.062
Multi-Family	Indicator equal to 1 if the loan is collateralized by multi-family property, 0 otherwise	Schedule H.2 and third-party data vendor	-0.175	0.040
Office	Indicator equal to 1 if the loan is collateralized by office property, 0 otherwise	Schedule H.2 and third-party data vendor	-0.154	0.028
Past Maturity	Indicator equal to 1 if the loan is past its reported maturity date, 0 otherwise	Schedule H.2 and third-party data vendor	2.767	0.055
At Maturity	Indicator equal to 1 if the loan is in the quarter of its reported maturity date, 0 otherwise	Schedule H.2 and third-party data vendor	5.515	0.054
1 to 4 Quarters from Maturity	Indicator equal to 1 if the loan is between 1 and 4 quarters from its reported maturity date	Schedule H.2 and third-party data vendor	2.067	0.018
5 to 8 Quarters from Maturity	Indicator equal to 1 if the loan is between 5 and 8 quarters from its reported maturity date	Schedule H.2 and third-party data vendor	0.248	0.028
LTV at Origination	Loan-to-value origination reported at the loan's origination date	Schedule H.2 and third-party data vendor	1.425	0.040
Multi-Family CMBS	Indicator equal to 1 if the loan is a CMBS loan collateralized by multi-family property, 0 otherwise	Third-party data vendor	0.385	0.040

Variable	Transformation	Source	Estimate	Standard Error
FR Y-14 Income Producing At Maturity	Indicator equal to 1 if the loan is a FR Y-14 income producing-loan in the quarter of its reported maturity, 0 otherwise	Schedule H.2	-1.911	0.072
FR Y-14 Construction At Maturity	Indicator equal to 1 if the loan is a FR Y-14 construction loan in the quarter of its reported maturity, 0 otherwise	Schedule H.2	-2.509	0.085
BBB Spread	Difference between the U.S. BBB corporate bond yield and the U.S. 10-year treasury rate	Board Stress Test Scenario	0.001	0.0001
Unemployment Rate	County-level unemployment rate	Auxiliary Translation of Board Stress Test Scenario	0.117	0.003
Vacancy Rate	Market and property-type-level vacancy rate	Third-party data vendor	0.069	0.003
CRE Price Index	Market and property-type-level CRE price index, expressed as change from loan origination	Third-party data vendor	-1.066	0.039
CRE Rent Index	Market and property-type-level CRE rent index, expressed as change from loan origination	Third-party data vendor	-0.561	0.076
House Price Index	County-level house price index, expressed as year-over-year change	Auxiliary Translation of Board Stress Test Scenario	-3.304	0.104

The Board proceeds with the following steps to project $\widehat{PD}_{i,t}$ for the set of loans reported on Schedule H.2 by firms.

Projecting PD from the Logistic Regression Model

First, the Board classifies certain loans as observed in default as of the reporting date used for a given supervisory stress test. Loans that are reported at least 90 days past due, placed on non-accrual status, or extended with a rating equivalent to CCC or below are considered in default. Such loans are assigned $\widehat{PD}_{i,t} = 1$. For all remaining (non-default) loans, the Board combines the estimated coefficients from Table B1 with loan characteristics reported on Schedule H.2, the published macroeconomic scenario, scenario projections of CRE market conditions,[60] and scenario projections of regional unemployment rate and house price index to project loan-level quarterly ($\widehat{PD}_{i,t}$) through the stress horizon. See Section III.B of the Enhanced Transparency and Public Accountability Proposal for details on how the national scenario paths are used to produce projections of sub-national unemployment rate and house price index.

DSCR Adjustment

DSCR, a key underwriting metric and a commonly used measure of loan sensitivity to interest payments, is an important determinant of refinancing default risk.[61] DSCR is important for the CRE PD model because most CRE loans on income-producing properties are not fully amortizing and often have a significant balloon payment due at maturity. The standard practice is to roll this ballon payment over into a refinance loan, and lenders generally require a minimum DSCR between 1.2 and 1.5 to qualify for a loan (depending on various factors such as property type, collateral value, borrower creditworthiness, and market conditions).

After $\widehat{PD}_{i,t}$ is calculated for each loan-quarter, the model-projected PD for a subset of loans—income producing loans that approach maturity with DSCR below 1.2 (a typical

[60] *See* Section B.ii.d for more details regarding the translation of the published macroeconomic scenario into projections for CRE market conditions.

[61] *See* Ciochetti, B., Deng, Y., Gail, L., Shilling, J., & Yao, R., 2003. A Proportional Hazards Model of Commercial Mortgage Default with Originator Bias (Journal of Real Estate Finance and Economics).; Cho, H., Ciochetti, B., Shilling, J., 2013. Are Commercial Mortgage Defaults Affected by Tax Considerations (Journal of Real Estate Finance and Economics); Glascock, J., & Lu-Andrews, R., 2014. Am Examination of Macroeconomic Effects on the Liquidity of REITs (Journal of Real Estate Finance and Economics).

minimum underwriting threshold)—is adjusted upwards by a factor of four, to account for the tendency of the logistic regression model to underpredict PD for such loans:[62]

Equation B3 – Model-Projected Probability of Default, Adjusted for DSCR

$$\widehat{PD}_{i,t}^{*} = \begin{cases} 4 * \widehat{PD}_{i,t} \; if \; DSCR < 1.2 \; or \; missing \; and \; loan \; i \; matures \; in \; t = \{1, \dots, 9\} \\ \widehat{PD}_{i,t} \qquad otherwise \end{cases}$$

where $\widehat{PD}_{i,t}$ is the model-projected PD for loan i in projection quarter t. In other words, the 4x scalar is applied only to income-producing loans that reach maturity over the projection horizon (i.e., within the next nine quarters) if DSCR < 1.2 or is missing in any projection quarters (excluding t_0).

DSCR at t_0 (the reporting date associated with a given stress test event) is computed as the ratio of net operating income (NOI) to interest payments:

Equation B4 – DSCR Calculation at t_0

$$DSCR_{t=t_0} = \frac{Net \; Operating \; Income \; Amount_{t_0}}{Outstanding \; Balance_{t_0} \times Reported \; Interest \; Rate_{t_0}}$$

DSCR is then updated throughout the stress horizon based on path of the Prime Rate (PR) variable from the Board's published stress test scenario:

Equation B5 – DSCR Calculation through the Stress Horizon

$$DSCR_t = \frac{Net \; Operating \; Income \; Amount_{t_0}}{Outstanding \; Balance_{t_0} \times \max \{Reported \; Interest \; Rate_{t_0} + (PR_t - PR_{t_0}), \; 0.01\}}$$

Next, upper and lower bounds of 0.9 (90 percent) and 0.001 (0.1 percent) are imposed on the DSCR-adjusted, model-projected PD ($\widehat{PD}_{i,t}^{*}$).

Assigning Synthetic PDs for Low-Information Loans

[62] For more background on the calibration of the DSCR adjustment, see section B.ii.a.(2).

Finally, for loans that are not reported with sufficient information to produce model-projected PD, the Board assigns a conservative, synthetic PD based on the 90th percentile of the distribution of projected $\widehat{PD}^*_{i,t}$ for observations of the same loan type, property type, and projection quarter.

(2) Rationale

Reduced Form Approach: Logistic Regression Model

The CRE PD model sub-component takes a reduced form approach by modeling PD based on its estimated statistical relationship with loan characteristics and macroeconomic factors. The model is specified as a logistic regression, which assumes that PD is logistically distributed and thus that the cumulative PD ranges between zero and one. Logistic regression is a technique for modeling probabilities of a binary outcome variable—a variable that can take on only one of two possible values—like loan default (i.e., a loan either goes into default or it does not). The framework has been widely used to model credit risk in the literature.[63]

The decision to use a reduced form approach, and the choice to specify the model as a logistic regression, align with the Board's Stress Testing Policy Statement, which in turn facilitate an assessment that can evaluate whether the largest and most complex financial firms are sufficiently capitalized to absorb losses in stressful economic conditions while continuing to meet obligations to creditors and other counterparties and to lend to households and businesses. The reduced form logistic regression framework is forward-looking; it is well-defined under

[63] *See* Altman, E., & Saunders, A., 1998. Credit Risk Measurement: Developments Over the Last 20 Years (Journal of Banking & Finance), 1721-1742; Episcopos, A., Pericli, A., & Hu, J., 1998. Commercial Mortgage Defaults: A Comparison of Logit with Radial Basis Function Networks (Journal of Real Estate Finance & Economics), 163-178; Ambrose, B., & Saunders, A., 2003. Commercial Mortgage-Backed Securities: Prepayment and Default (Journal of Real Estate Finance and Economics) 26:2/3, 179-196; Chen, J., & Deng, Y., 2013. Commercial Mortgage Workout Strategy and Conditional Default Probability: Evidence from Special Serviced CMBS Loans (Journal of Real Estate Finance & Economics), 46, 609-632.

various macroeconomic scenarios.[64] Additionally, under a reduced form approach, the model can be calibrated using data on many types of CRE loans and allows for the choice of independent variables that limit any time- or firm-specific effects, following the Board's principle of consistency and comparability from the Stress Testing Policy Statement.[65] The logistic regression framework is simple, as it links the PD to a linear combination[66] of the independent variables. This allows for a straightforward interpretation of the impact of varying macroeconomic conditions under stress on model outcomes. Finally, the logistic regression framework enables the CRE model to capture risks that arise in times of stress by allowing for a range of independent variables that include both continuous and discrete drivers of loan performance.

Independent Variable Selection

The logistic regression used for the CRE PD model sub-component includes loan characteristics and measures of local and aggregate economic conditions as independent variables that the Board has determined best capture drivers of CRE loan default risk. The variable selection process was based on a combination of economic theory and statistical relevance. As shown in Table B1, the estimated coefficients of all independent variables have signs in the direction expected by economic theory and are statistically significant. Further rationale for the inclusion of each of the independent variables is described below.

- **Loan age:** Age is included to reflect that the baseline default risk for a loan is dynamic (that is, fundamentals can evolve from the time of underwriting throughout the loan's lifetime). A cubic polynomial of loan age is used to recognize that the relationship between age and default is non-linear, with multiple periods of heightened risk.
- **Loan type:** Loan type indicators are included to account for differences in default risk between (1) firm-held (Schedule H.2) loans and securitized (CMBS) loans, and (2) firm-

[64] *See* Stress Testing Policy Statement.
[65] *See* Stress Testing Policy Statement.
[66] A linear combination of a set of terms involves multiplying each term by a scalar (in this case, the estimated coefficient) and adding the results together.

held income-producing loans and bank-held construction loans. See Section B.ii.a.(4) for further discussion on the inclusion of CMBS loans in the estimation sample.

- **Loan characteristics:** Empirical academic literature has found the importance of loan-specific characteristics in explaining commercial mortgage default. Loan-specific characteristics explored in the literature include underwriting terms like loan-to-value (LTV) ratio, DSCR, loan size, prepayment incentive, property type, loan covenants (prepayment constraints), and more.[67] The Board has chosen to include LTV ratio and property type indicators in the logistic regression specification while DSCR is captured separately via the DSCR adjustment. The inclusion of these characteristics positively influences model fit and forecasting performance, while coefficients are readily interpretable and estimated with precision.
- **Proximity to maturity indicators:** The proximity of a loan to maturity is a key driver of default risk for CRE loans. Most CRE loans on income-producing properties are not fully amortizing. Construction loans typically have increasing outstanding balance over the life of the loan, as the project advances and the builder continues to draw on the committed amount. As a result, CRE loans typically feature "balloon payments," whereby a significant portion of the original principal is due at maturity. A balloon payment is typically rolled over into a refinanced loan, either with the current lender, another portfolio lender, or in the CMBS market. Construction loans are also dependent on take-out financing upon completion, whereby the outstanding balance is rolled over into a new mortgage on the completed building. Accordingly, important negotiations occur around the maturity date of a CRE loan. The quarters leading up to maturity are a time of high risk for loan default, especially if property values have fallen, cash flows have decreased, and/or interest rates have risen. Borrowers may choose to default at maturity if they are facing a significant increase in borrowing costs or if asked to provide additional equity to successfully refinance. Interaction terms are also included to capture the differences in maturity risk between firm-held (Schedule H.2) loans and CMBS loans.
- **Macroeconomic conditions**: Academic literature has shown the importance of both aggregate and local macroeconomic conditions for the likelihood of CRE loan default.[68] BBB spread is included in the CRE PD model component to capture the general market view of risk for wholesale credit. Additionally, local (county-level) house price index (HPI) and unemployment rate are included to account for the importance of local economic conditions on CRE property performance. The Board estimates coefficients for

[67] *See* Goldberg, L., & Capone Jr., C., 2002. A Dynamic Double-Trigger Model of Multifamily Mortgage Default (Real Estate Economics) 30, 85-113; Ciochetti, B., Deng, Y., Gao, B., & Yao, R., 2002. The Termination of Commercial Mortgage Contracts through Prepayment and Default: A Proportional Hazard Approach with Competing Risks (Real Estate Economics) 30:4, 595-633; Ciochetti, B., Deng, Y., Gail, L., Shilling, J., & Yao, R., 2004. A Proportional Hazards Model of Commercial Mortgage Default with Originator Bias (Journal of Real Estate Finance and Economics); Ambrose, B., & Saunders, A., 2003. Commercial Mortgage-Backed Securities: Prepayment and Default (Journal of Real Estate Finance and Economics) 26:2/3, 179-196.

[68] *See* Ambrose, B., & Saunders, A., 2003. Commercial Mortgage-Backed Securities: Prepayment and Default (Journal of Real Estate Finance and Economics) 26:2/3, 179-196; Archer, W., Elmer, P., Harrison., D., & Ling., D., 2002. Determinants of Multifamily Mortgage Default (Real Estate Economics) V30:3, 445-473; Titman, S., & Tsyplakov, S., 2010. Originator Performance, CMBS Structures, and the Risk of Commercial Mortgages.; Chen, J., & Deng, Y., 2013. Commercial Mortgage Workout Strategy and Conditional Default Probability: Evidence from Special Serviced CMBS Loans (Journal of Real Estate Finance & Economics), 46, 609-632.

these factors with the expected signs; the inclusion of these risk drivers facilitates model outcomes that are sensitive to the various stress test scenarios.

- **CRE market conditions**: Additional research has documented a significant correlation between local CRE market conditions and loan defaults.[69] The Board includes information on local market and property-type-level fundamentals such as CRE prices, vacancies, and rents in the CRE PD model. The Board found that each of these variables improves model fit and, in particular, the model's ability to capture variations in default risk across property types and locations.

Other independent variables that have been theorized and/or shown to influence CRE loan default include loan characteristics such as prepayment penalties, loan size, loan term, covenants, and borrower type; property characteristics such as transaction costs, taxes, insurance, reported occupancy rate of the property, and capitalization rate;[70] and other macroeconomic variables like yield curve slope, interest rate, volatility, legal environment, and more.[71] The Board explored the use of such alternative variables but ultimately chose the specification described above due to the availability of data, quality of data, coefficient interpretability, model stability, and statistical significance.

DSCR Adjustment

The Board adjusts the output of the logistic regression with a scaling factor based on the DSCR of the loan. This adjustment allows the CRE PD model subcomponent to account for the effect of changes in interest rates on the default probability of a CRE loan. This is especially

[69] *See* An, X., Deng, Y., Nichols, J., & Saunders, A., 2013. Local Traits and Securitized Commercial Mortgage Defaults (Journal of Real Estate Finance & Economics) 47, 787-813.
[70] *See* Goldberg, L., & Capone Jr., C., 2002. A Dynamic Double-Trigger Model of Multifamily Mortgage Default (Real Estate Economics) 30, 85-113; Ciochetti, B., Deng, Y., Gao, B., & Yao, R., 2002. The Termination of Commercial Mortgage Contracts through Prepayment and Default: A Proportional Hazard Approach with Competing Risks (Real Estate Economics) 30:4, 595-633; Ciochetti, B., Deng, Y., Gail, L., Shilling, J., & Yao, R., 2003. A Proportional Hazards Model of Commercial Mortgage Default with Originator Bias (Journal of Real Estate Finance and Economics).; Ambrose, B., & Saunders, A., 2003. Commercial Mortgage-Backed Securities: Prepayment and Default (Journal of Real Estate Finance and Economics) 26:2/3, 179-196.
[71] *See* Ambrose, B., & Saunders, A., 2003; Archer, W., Elmer, P., Harrison., D., & Ling., D., 2002. Determinants of Multifamily Mortgage Default (Real Estate Economics) V30:3, 445-473; Titman, S., & Tsyplakov, S., 2010. Originator Performance, CMBS Structures, and the Risk of Commercial Mortgages.

important because the model parameters are estimated using Schedule H.2 data from 2009 to 2018, a period during which interest rates were persistently low and thus provided little empirical variation to meaningfully estimate sensitivity.[72]

In recent years, due to high interest rates, DSCR for Schedule H.2 loans decreased to levels below those during the pre-pandemic period for all property types, increasing the share of loans near maturity with a DSCR low enough to preclude refinancing and therefore engender default. While the logistic regression model captures the effect of interest rates on refinancing risk indirectly via indicator variables measuring a loan's proximity to maturity, the model implicitly assumes that loans with low DSCR face the same refinancing risk as loans with high DSCR, all else equal. Given that the model parameters were estimated using a historical period with persistently low interest rates (that is, with a small share of loans approaching maturity with low DSCR), there is risk that the model might underestimate PD for close-to-maturity low DSCR loans.

Without the DSCR adjustment, the model's sole reliance on proximity to maturity does not currently discriminate well between low DSCR (DSCR < 1.2) and high DSCR (DSCR ≥ 1.2) loans.[73] Specifically, the logistic regression model predicts slightly lower PD for low DSCR loans. The empirical evidence, however, suggests that the default rate for loans approaching maturity with low DSCR is much higher than that for loans approaching maturity with high

[72] 2009 is the earliest period in which Schedule H.2 data is available. Lengthening the sample beyond the end of the current period would introduce complicating factors that would result in potentially unreliable estimates. More specifically, macroeconomic conditions experienced sharp movements during the COVID-19 pandemic that were decoupled from credit risk and CRE market conditions. Including such data in the estimation sample would attenuate the estimated sensitivity of default probability to macroeconomic conditions.

[73] Given that it is likely for the lender to work with the borrower if the borrower can at least service the interest payment, the lower end of the common underwriting threshold (i.e., DSCR of 1.2) was chosen as the threshold for low DSCR. The Federal Reserve believes that using DSCR < 1.2 as a threshold for low versus high DSCR is appropriate because it allows the model to capture the effect of high interest rates on refinancing risk for CRE loans that are most at risk (i.e., those approaching maturity with an underwriting metric that is poorer than the general minimum underwriting standard).

DSCR. In addition, out-of-sample performance testing results confirm that the logistic regression model underpredicts PD for loans approaching maturity with low DSCR during both low and high interest rate environments. Taken together, these findings suggest that the logistic regression model does not appropriately capture the refinancing risk of low-DSCR loans. As a result, the Board applies the DSCR-based adjustment to address the risk that the model might underestimate PD for low DSCR loans.

The choice of the 4x multiplier in the DSCR adjustment step was informed by the degree of the logistic regression model's underprediction—the ratio of realized (historical) default rate to predicted default rate as well as the ratio of historical default rate for loans approaching maturity with DSCR < 1.2 to that with DSCR ≥ 1.2. During the period from 2022Q1 to 2024Q3, the degree of the model's underprediction was approximately 4x. In addition, the empirical default rate for loans approaching maturity with DSCR < 1.2 is approximately 4x higher than loans approaching maturity with DSCR > 1.2 in the recent high-interest rate period.

Without the DSCR adjustment, on average, the logistic regression model projects slightly lower PD for low DSCR loans than for high DSCR loans. With the DSCR adjustment (4x multiplier), the average projected PD value for loans with DSCR < 1.2 is about 3–4 times higher than those with DSCR ≥ 1.2, which is the center of the empirical distribution. The Board also considered interacting DSCR with proximity to maturity indicators as an alternative approach to capturing this effect, but there is not enough variation in interest rates over the estimation sample period to consistently estimate this effect. In addition, DSCR is not available for construction loans, which are pooled with income-producing loans in the estimation sample.

(3) Data and Data Adjustments

Data Sources

A summary of datasets used in the CRE PD model sub-component is provided in Table B2.

Table B2 - Datasets used in the CRE PD model sub-component

Name	Description	Type
Schedule H.2	Quarterly, facility-level regulatory report that was first collected in 2011Q3, though limited information is available back through 2009Q4	Regulatory
CMBS data (third-party vendor)	Loan-level dataset containing historical performance information on CRE loans that underly CMBS deals	Vendor
CRE Market Data (third-party vendor)	Historical data on CRE market fundamentals by geographic market and property type	Vendor
Macroeconomic Scenario Data	Historical and hypothetical scenario data on macroeconomic drivers at the county, state, and national levels.	Various sources (see “Notes Regarding Scenario Variables” in 2025 Supervisory Stress Test Scenarios publication)
ZIP code-to-county map (third-party vendor)	Map from U.S. ZIP codes to county codes	Vendor
Rating Concordance Map	Firm-submitted mappings from internal rating scales to equivalent external ratings	Regulatory

Data Adjustments

The dataset used to estimate the logistic regression specified in Equation B2 and Table B1 is a loan-level dataset comprising loans from two historical sources: bank portfolio-held loans reported on Schedule H.2 and securitized loans (underlying CMBS products) provided by a third-party data vendor. These sources are pooled together to create a panel of quarterly loan performance history from 1998Q1 to 2018Q4. Additional historical information on macroeconomic and CRE market conditions are joined to the pooled loan history to provide the full data necessary to estimate the regression specified in Equation B2 and Table B1. The Board implements several data filtering and adjustment steps on the source datasets listed in Table B2 to obtain an estimation dataset suitable for calibrating the model coefficients. These steps are summarized below. The adjustments described below ensure that the model coefficients are estimated accurately and with precision, and that the resulting fit of the model is not unnecessarily hindered due to mis-reported data and/or outlier observations.

CMBS Loan Data

The history of CMBS loans is provided at a monthly frequency by a third-party data vendor. The Board keeps only end-of-quarter observations from this dataset to align with the quarterly frequency of Schedule H.2. The default indicator for CMBS loans is constructed based on the earliest quarter in which the loan is reported with a status of at least 90 days past due, foreclosed, liquidated, real estate owned (REO), or transferred to special servicing;[74] the default indicator for this observation is set to a value of one. The default indicator for all prior quarterly observations for the corresponding loan are set to zero, and all subsequent observations are removed from the estimation sample. In addition, CMBS loan observations after the earliest quarter in which the loan is fully paid are removed from the estimation sample. Also, CMBS loans for which the first available observation is reported as defeased, liquidated, foreclosed, paid off, at least 90 days past due, or in special servicing are entirely excluded from the estimation sample. Such observations are excluded because these conditions preclude an initial

[74] In the event of loan distress, CMBS loans are transferred from the master servicer to a special servicer – a third party that works to resolve distress through loan modification or workout. Occasionally, troubled loans are transferred to special servicing even before payments are significantly past due. Such events signal that the master servicer suspects the borrower will have difficulty repaying the loan balance in the future. The Board includes special servicing as a sufficient condition to identify CMBS loan default to capture this phenomenon.

transition from current to default in the future, which is the transition that the model is intended to capture.

Schedule H.2 Loan Data

The Board implements several data adjustments specific to loans reported on Schedule H.2. First, the Board identifies consistent histories for each loan based on the contemporaneous and prior reported loan numbers for each observation. A time-invariant, derived loan number is then assigned to link the entire history for a common loan. The default indicator for Schedule H.2 loans is constructed based on the earliest quarter in which the loan is reported as at least 90 days past due, has transitioned to non-accrual status, or is extended with a rating equivalent to CCC or below; the default indicator for this observation is set to a value of one. The default indicator for all prior quarterly observations for the corresponding loan are set to zero, and all subsequent observations are removed from the estimation sample. Such observations are excluded because these conditions preclude an initial transition from current to default in the future, which is the transition that the model is intended to capture.

The Board implements logic to ensure that loan characteristics at the time of loan origination are held constant over the life of the loan. Specifically, if at-origination loan characteristics are reported to change value over the life of the loan or are reported missing in subsequent quarters, the Board maintains the earliest reported value for the loan in the estimation sample. Such variables include the original committed balance, origination date of the loan, and the original reported location, value, and property type of the collateral. This adjustment ensures that at-origination values entering the model reflect the loan characteristics at the time of underwriting rather than potentially erroneous values.

Local Macroeconomic Data

Historical county-level macroeconomic characteristics (unemployment rate and HPI) are joined to the pooled loan dataset by mapping the loan's reported location (ZIP code) to county characteristics in the macroeconomic data.

CRE Market Conditions

CRE market conditions (rent index, price level, and vacancy rate) by market and property type, provided by a third-party data vendor, are first seasonally adjusted using the X11 procedure—a common method used for removing the seasonal component from a time series.[75] The seasonally adjusted CRE market variables are then joined to the pooled loan dataset by mapping the loan's reported location to the vendor's geographic markets and by mapping the loan's reported property type to the property types provided by vendor.[76] After matching the loan's history with the time series provided by vendor, for each loan, the Board computes the change in the rent and price indices from the time of loan origination.

Extreme Value Filtering

Several extreme value filters are applied to the estimation sample. Loan observations where values are outside of the range reported in Table B3 are excluded from the estimation sample. These observations are excluded to ensure that the model coefficients are estimated accurately and that the resulting fit of the model is not unnecessarily hindered due to mis-reported data and/or outlier observations.

[75] Certain time series provided by the third-party data vendor contain significant seasonality (e.g., hotel and multi-family vacancy rates). Seasonal adjustment is applied for consistency and comparability with other, published macroeconomic scenario variables that are seasonally adjusted (e.g., unemployment rate, house price index).
[76] Loans reported under property type options that are not reported by the vendor are either assigned an average of provided property types (Mixed, Land and Lot Development, Other, Healthcare), or are assigned to the multi-family series (Homebuilders except condo, Condo/Co-op).

Table B3 - Extreme value filters applied to the PD estimation sample

Variable	Minimum Value	Maximum Value
Vacancy Rate	1%	35%
CRE Rent Index (change from loan origination)	-50%	50%
CRE Price Index (change from loan origination)	-50%	150%
Unemployment Rate	n/a	15%
LTV at Origination	10%	150%
Current Value	$500,000	$500,000,000
Original Value	$500,000	$500,000,000
Cumulative Charge-offs	n/a	$500,000,000
Origination Date	1980Q1	n/a
Last Valuation Date	1980Q1	n/a
Last NOI Date	1980Q1	n/a

(4) Assumptions and Limitations

The Board makes certain assumptions in the PD model subcomponent that the Board believes are appropriate to ensure that the model is robust, stable, and fit for purpose. The time range over which the model parameters are estimated and from which Schedule H.2 data is available, 2009Q4 to 2018Q4, includes only a small amount of variation in macroeconomic conditions. As a result, loan-level data from the CMBS market, provided by a third-party data vendor for the period 1998Q1 to 2018Q4, is used to supplement the available Schedule H.2 data to estimate the PD model parameters. Certain characteristics that predict loan default can also drive the selection of loans into CMBS and bank portfolios (that is, assignment is not random), and these loans can perform differently over time and over different states of the economy. The Board's PD model specification has been designed to control for these differences between loan types, ensuring the reliability of coefficient estimates. While this issue could be avoided by using a Schedule H.2 firm-only sample, there are several reasons why the Board has chosen the pooled sample.

The Board began collecting Schedule H.2 in 2012. Therefore, only firm loans that were originated after 2012 or were originated before the collection begins and survived through that date are observable in the data set. This introduces survivorship bias into the firm-only sample; that is, loans that were originated prior to 2012 and exited the sample prior to the collection cannot be observed. By comparison, the CMBS data have a much longer sample period that includes two full business cycles, a period of stress spanning the entire great financial crisis, and no issues of survivorship bias.

Using only the short sample period for Schedule H.2 loans would lead to less reliable and less precise coefficient estimates. An estimation sample based on only Schedule H.2 loans leads to significantly different coefficient estimates and results that are not straightforward to interpret.

Many of the key summary statistics of the loan-level independent variables included in the model are generally similar across Schedule H.2 and CMBS loan samples. The most important differences between bank and CMBS loans are observed as loans approach maturity. CMBS loans are much more likely to default at maturity than firm loans. This is likely driven by the tendency of firms to renegotiate with borrowers.[77] The logistic regression model controls for these differences in maturity risk by interacting the proximity-to-maturity indicators with indicator variables for both Schedule H.2 income-producing and construction loans.

In summary, the limitations of using a sample based on only Schedule H.2 data outweigh the benefits. The Board regularly monitors the evolution of loan performance in both the CMBS

[77] For example, research shows that bank lenders are more likely to renegotiate distressed loans than are CMBS investors. *See* Black, L., Krainer, J., & Nichols., J., 2016. From Origination to Renegotiation: A Comparison of Portfolio and Securitized Commercial Real Estate Loans (Journal of Real Estate Finance & Economics), 55:1, 1-31.

and Schedule H.2 data sets to assess whether the implementation of a Schedule H.2 (firm-only) model is feasible given new data.

The Board considered extending the PD estimation sample beyond 2018Q4, but data from the COVID-19 pandemic era is characterized by unprecedented movements in macroeconomic variables that result in attenuation of the sensitivity of the PD model to various macroeconomic scenarios. In addition, the timing and magnitude of loan performance between CMBS and Schedule H.2 loans diverged in the pandemic era.

The PD model sub-component also applies the same model specification for both income-producing and construction loans. The Board considered a wide range of alternative specifications to further capture any differential impact of risk drivers between types of loans, but the chosen approach assumes that the model's basic functional form is appropriate for both income-producing and construction loans. The modeling of construction loans is a significant challenge for both academics and practitioners in CRE modeling due to the scarcity of historical data. The lack of any construction loans in CMBS and limited information in other datasets has posed a significant challenge to modeling default risk for construction loans. Specifically, the limited time period over which historical construction data is available contains little macroeconomic variation and thus hinders the estimation of sensitivity to various macroeconomic conditions. Pooling construction loans together with income-producing loans in the logistic regression specification enables projections for construction loans that are forward-looking and capable of evaluating the impact of severe economic stress, aligning with Stress Testing Policy Statement.

(5) Alternative Approaches

The Board considered alternative approaches to estimating PD for the CRE Model, including the Cox proportional hazards model. The Cox proportional hazards model is an alternative framework commonly used in credit risk modeling to predict PD. The central assumption of the proportional hazards framework is that the effect of a change in each independent variable on PD is proportional to the baseline hazard rate (a non-parametric function of the age of the loan). The Board considered using this framework instead of logistic regression but determined it is inferior to the logistic regression framework in this application because of three main issues: (1) the non-parametric baseline hazard function is not flexible enough to address the different loan structures present in the data, (2) the proportionality assumption is too restrictive for certain variables that have differential impacts on PD at different points in the loan's lifetime, and (3) predictions from the proportional hazards model are not bound in the range of 0 to 1.[78]

The Board considered increasing the segmentation of the model to allow for additional heterogeneity in sensitivity to market conditions across property types. CRE loans are collateralized by multiple building types, which are subject to different market conditions and have different investor and tenant bases. The Board found that increased segmentation minimally improved model performance but introduced data idiosyncrasies—in certain segments with limited observations—that result in spurious outcomes. Segmentation by property type would necessitate additional adjustments, conflicting with the Board's stated principle of simplicity.

[78] When independent variables deviate from their historical ranges, modeled PD can be greater than one.

The PD for a commercial mortgage is largely a function of the current and future cash flows expected to be generated by the property. Shocks to these cash flows can lead to default, either directly if the shocks are sufficiently large as to prevent the borrower from servicing their debt,[79] or indirectly by incentivizing the borrower to exercise the put option implicit in the mortgage contract, that is, to strategically default.[80] Other approaches for estimating PD follow more structural modeling techniques that are generally based on the view of mortgage default as a put option for the borrower. See, for example, Kau et al., who develop a framework to estimate the level of current LTV ratio that triggers default, where property values evolve by region and property type.[81] Goldberg & Capone develop a "double trigger" approach to modeling the borrower's default option that considers levels of both DSCR and current LTV ratio.[82] Such approaches have limited sensitivity to macroeconomic conditions and are much more operationally complex than the Board's chosen reduced form approach.

(6) Questions

Question B1: The Board seeks comment on the alternative of using a structural modeling approach, e.g., one based directly on DSCR and LTV, as compared to the Board's current approach of a logistic regression model?

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[79] *See* Goldberg, L., & Capone Jr., C., 2002. A Dynamic Double-Trigger Model of Multifamily Mortgage Default (Real Estate Economics) 30, 85-113; Seslen, T., & Wheaton, W., 2010. Contemporaneous Loan Stress and Termination Risk in the CMBS Pool: How "Ruthless" is Default? (Real Estate Economics) V38:2, 225-255.

[80] *See* Titman, S., & Torous, W., 1989. Valuing Commercial Real Estate Mortgages: An Empirical Investigation of Contingent-Claims Approach to Pricing (The Journal of Finance) V44:2, 345-373; Vandell, K., Barnes, W., Hartzell, D., & Wendt, W., 1993. Commercial Mortgage Defaults: Proportional Hazards Estimation Using Individual Loan Histories (Journal of the American Real Estate and Urban Economics Association), V21:4, 451-480; Quigley, J., & Van Order, R., 1995. Explicit Tests of Contingent Claims Model of Mortgage Default (Journal of Real Estate Finance & Economics) 11, 99-117.

[81] *See* Kau, J., Keenan, D., & Yildirim, Y., 2008. Estimating Default Probabilities Implicit in Commercial Mortgage Backed Securities (CBMS) (Journal of Real Estate Finance and Economics), V39, 107-117.

[82] *See* Goldberg, L., & Capone Jr., C., 2002. A Dynamic Double-Trigger Model of Multifamily Mortgage Default (Real Estate Economics) 30, 85-113.

Question B2: The Board seeks comment on additional factors that should be considered in the PD model as compared to the set of factors currently included in the Board's specification.

Question B3: The Board seeks comment on its use of CMBS data to supplement the Schedule H.2 sample in estimation of the PD model, as compared to the alternative of using the Schedule H.2 sample only (or in combination with another supplementary dataset).

Question B4: The Board seeks comment on the use of a model pooled across loan types and property types, as compared to an alternative that is segmented along these dimensions.

Question B5: The Board seeks comment on its use of data through 2018Q4 to estimate the PD model coefficients, as compared to the alternative of also using data after 2018Q4.

b. *LGD Model Sub-Component*

The loss given default (LGD) model sub-component calculates the loss conditional on a default by using the structural relationship between LGD, the property value, and the loan's committed balance at the time of default. The model sub-component projects the loan's collateral value at the time of default using loan-specific valuations, movements in broader commercial price indices, and a discount factor that captures the price discount on properties sold to resolve distressed bank debt. The discount factor is estimated separately by property type from industrywide realized transaction data on CRE assets.

(1) Model Specification

The LGD model sub-component projects the loss amount (as a share of loan balance at the start of the projection horizon) that each loan i is expected to experience in each quarter t, conditional on default ($\widehat{LGD}_{i,t}$). The model is built on the structural relationship between LGD, the property value, and the loan's committed balance at the time of default:

Equation B6 – LGD Projection

$$LGD_{i,t} = 1 - \frac{V_{i,t}}{C_{i,t}}$$

where $V_{i,t}$ is the projected value of the collateral at the time of default and $C_{i,t}$ is the committed balance of loan i at time t.

The facility's committed balance ($C_{i,t}$) is assumed to be known at the time of default based on information reported on Schedule H.2. The model projects the loan's collateral value at the time of default ($V_{i,t}$) using the below equation:

Equation B7 – Collateral Value Projection

$$V_{i,t} = V_{i,t=orig} \times \left(\frac{ScenarioCREPrice_t}{HistoricalCREPrice_{t=orig}}\right) \times (1 - \widehat{DF}_p)$$

where $V_{i,t=orig}$ is the reported value at origination for loan i, $\left(\frac{ScenarioCREPrice_t}{HistoricalCREPrice_{t=orig}}\right)$ represents the change in the U.S. CRE price index[83] from the time of loan origination to the time of default (in the hypothetical scenario), and $\widehat{DF}_p$ is a discount factor, differentiated by property type p, that captures the price discount on properties sold to resolve distressed bank debt.

The discount factor is estimated separately by property type, using a modification of the standard repeat-sales regression framework.

Equation B8 – Discount Factor Regression Specification

$$ln\left(\frac{p_{i,t}}{p_{i,s}}\right) = \alpha + \beta_d\left(DistressedLoan_{i,t}\right) + \beta_{d,ltv}\left(DistressedLoan_{i,t} \times LTV_{i,s}\right) + \sum_{\tau=\tau_0}^{T} \beta_\tau D_{i,\tau} + u_{i,t,s}$$

[83] The U.S. CRE price index published in the Federal Reserve's stress test scenario and used in the CRE LGD model is a single index that is aggregated across multiple U.S. property types and geographies.

where $p_{i,t}$ is the sale price of property i in period t; $p_{i,s}$ is the purchase price of property i in period $s < t$; $Distressed\ Loan_{i,t}$ is an indicator variable denoting whether the sale of property i at time t resolved a stress loan situation; $LTV_{i,s}$ is the LTV at origination for the loan financing the acquisition of property i in period s; and $D_{i,\tau}$ is a time indicator variable equaling -1 if the property was purchased in that year-quarter (i.e., $\tau = s$), 1 if the property was sold in that year quarter (i.e., $\tau = t$), and 0 otherwise.

The discount factor is computed from Equation B8 for each property type p:

Equation B9 – Discount Factor Calculation by Property Type

$$\widehat{DF}_p = 1 - e^{(\hat{\beta}_d + \hat{\beta}_{d,ltv} \times LTV)}$$

The model is estimated using historical CRE transaction data provided by a third-party data vendor. Coefficient estimates ($\hat{\beta}_d$, $\hat{\beta}_{d,ltv}$, and $\hat{\beta}_\tau$) are obtained via ordinary least squares. The resulting coefficient estimates for $\hat{\beta}_d$ and $\hat{\beta}_{d,ltv}$ are displayed in Table B4 (estimates for $\hat{\beta}_\tau$, which are not used in calculating model projections, are omitted for brevity).

Table B4 - Regression results for the discount factor equation in the LGD model sub-component.

Variable	Transformation	Source	Estimate	Standard Error
Construction Regression				
Distressed Loan	Indicator equal to 1 if the property was sold to resolve a distressed loan situation	Third-party data vendor	-0.678	0.109
Multi-Family Regression				
Distressed Loan	Indicator equal to 1 if the property was sold to resolve a distressed loan situation	Third-party data vendor	-0.516	0.022
Industrial Regression				
Distressed Loan	Indicator equal to 1 if the property was sold to	Third-party data vendor	-0.494	0.026

Variable	**Transformation**	**Source**	**Estimate**	**Standard Error**
	resolve a distressed loan situation			
Hotel Regression				
Distressed Loan	Indicator equal to 1 if the property was sold to resolve a distressed loan situation	Third-party data vendor	-0.927	0.077
LTV at Origination of Distressed Loan	Loan-to-value ratio reported at the property's acquisition date if the property was later sold to resolve a distress loan situation, 0 otherwise	Third-party data vendor	0.586	0.089
Office Regression				
Distressed Loan	Indicator equal to 1 if the property was sold to resolve a distressed loan situation	Third-party data vendor	-1.034	0.079
LTV at Origination of Distressed Loan	Loan-to-value ratio reported at the property's acquisition date if the property was later sold to resolve a distress loan situation, 0 otherwise	Third-party data vendor	0.611	0.091
Retail Regression				
Distressed Loan	Indicator equal to 1 if the property was sold to resolve a distressed loan situation	Third-party data vendor	-1.143	0.094
LTV at Origination of Distressed Loan	Loan-to-value ratio reported at the property's acquisition date if the property was later sold to resolve a distress loan situation, 0 otherwise	Third-party data vendor	0.710	0.111

The interaction term, $DistressedLoan_{i,t} \times LTV_{i,s}$, is only included in the discount factor specification for hotel, retail, and office properties. Model performance improves significantly when allowing the discount factors for hotel, retail, and office to vary with LTV at origination.

However, for other property types (multi-family, construction, and industrial), the interaction term is not statistically significant and does not have an impact on model performance.

After obtaining the estimated discount factors for each property type, the Board proceeds with projecting $\widehat{LGD}_{i,t}$ following Equations B6 and B7 for the set of loans reported on Schedule H.2.

Next, upper and lower bounds of 0.9 (90%) and 0.05 (5%) are imposed on the model-projected ($\widehat{LGD}_{i,t}$).

Finally, for loans that are not reported with sufficient information to produce model-projected LGD, the Board assigns a conservative, synthetic LGD based on the 90th percentile of the distribution of projected $\widehat{LGD}_{i,t}$ for observations of the same loan type, property type, and projection quarter.

(2) Rationale

The structural approach selected to model LGD, which ties projected LGD directly to LTV ratio, aligns with the Board's policies and principles for model development. These policies and principles support an assessment that can evaluate whether the largest and most complex financial firms are sufficiently capitalized to absorb losses in stressful economic conditions while continuing to meet obligations to creditors and other counterparties and to lend to households and businesses. The LGD model specification is forward-looking, has a structural approach that limits reliance on past outcomes, is well-defined under various macroeconomic scenarios, and does not include firm-specific fixed effects. The LGD model framework is simple, as it directly exploits the relationship between LGD and the LTV ratio of the loan, allowing for a straightforward interpretation of changes in model outcomes. Finally, the LGD model is robust and stable as changes in the model's outcomes are driven by underlying risk factors and varying macroeconomic scenarios rather than temporary variations in model performance.

Academic literature provides support for the selected model, particularly the choice of a structural approach, the use of LTV ratio as the key driver of LGD, the use of repeat-sales regression to estimate price discounts, and the decision to allow the price discount to vary with LTV ratio. Background literature providing context for each of these choices is described below.

Most of the existing literature on LGD in credit risk modeling has focused on reduced form approaches where LGD or recovery rate is regressed directly using either ordinary least squares,[84] censored regressions,[85] or two-stage mixture modeling approaches.[86]

Other studies have investigated indirect estimation of LGD. For example, Somers and Whittaker calculate LGD using the value of repossessed property, which is estimated using a quantile regression method.[87] Leow and Mues (2012), on the other hand, first estimate the probability of a defaulted loan undergoing repossession as a function of loan characteristics, estimate the discount in sale prices for a repossessed property as a function of loan characteristics, and then computed the predicted LGD using the projected probability of

[84] *See* Lekkas, V., Quigley, J., & Van Order, R., 1993. Loan Loss Severity and Optimal Mortgage Default (Journal of the American Real Estate and Urban Economics Association), V21:4, 353-371; Calem, P., & LaCour-Little, M., 2004. Risk-based Capital Requirements for Mortgage Loans (Journal of Banking & Finance), 28, 647-672; Qi, M., & Yang, X., 2009. Loss Given Default of High Loan-to-Value Residential Mortgages (Journal of Banking & Finance), 33, 788-799.
[85] *See* Yashkir, O., & Yashkir, Y., 2013. Loss Given Default Modelling: Comparative Analysis (Journal of Risk Model Validation), V7:1.
[86] *See* Hwang, R., Chung, H., & Chu, K., 2016. A Two-Stage Probit Model for Predicting Recovery Rates (Journal of Financial Services Research), 50:311, 311-339; Xiao, Y., Crook, J., & Andreeva, G., 2017. Enhancing Two-stage Modeling Methodology for Loss Given Default with Support Vector Machines (European Journal of Operational Research), V263:2, 679-689; Tanoue, Y., Kawada, A., & Yamashita, S., 2017. Forecasting Loss Given Default of Bank Loans with Multi-stage Model (International Journal of Forecasting), 33, 513-522; Tanoue, Y., Yamashita, S., 2019. Loss Given Default Estimation: A Two-stage Model with Classification Tree-based Boosting and Support Vector Logistic Regression (Journal of Risk), 21:4, 19-37.
[87] *See* Somers, M., & Whittaker, J., 2007. Quantile Regression for Modeling Distributions of Profit and Loss (European Journal of Operational Research), 183:3, 1477-1487.

repossession and the predicted discount in sale prices.[88] Tong, Mues, and Thomas model the incurred financial loss amount as a function of loan and macroeconomic characteristics and then compute LGD by dividing the predicted loss amount by the exposure at default.[89]

When estimating LGD (whether directly or indirectly), most of the published research considers both loan and macroeconomics characteristics as key factors. Examples of loan characteristics considered in the literature are LTV ratio at default, LTV ratio at origination, loan size, loan age, and property type; examples of macroeconomics factors affecting LGD include change in Commercial Property Price Index (CPPI), change in HPI, vacancy rate, and unemployment rate. Among these various risk factors, LTV ratio at default has been found to be the most important factor in determining the LGD value.[90] Conceptually, loans with higher LTV ratio at default have lower equity value, which leads to a lower recovery rate and thus higher LGD. In principle, one should be able to directly derive the LGD value if the true LTV ratio at default, timing of liquidation, liquidation expenses, and carrying costs are known.[91]

To estimate loss in a projected scenario, where liquidation is not observed, LTV ratio at default needs to be estimated. While the numerator (loan balance) is a function of prior loan payments, the denominator (property value) is unknown. For the estimation of property values, a number of studies suggest using a trend-based, mark-to-market valuation approach where the

[88] *See* Leow, M., & Mues, C., 2012. Predicting Loss Given Default (LGD) for Residential Mortgage Loans: A Two-stage Model and Empirical Evidence for UK Bank Data (International Journal of Forecasting) 28, 183-195.
[89] *See* Tong, E., Mues, C., & Thomas, L., 2013. A Zero-adjusted Gamma Model for Mortgage Loan Loss Given Default (International Journal of Forecasting), 29, 548-562.
[90] *See* Pennington-Cross, A., 2003. Subprime & Prime Mortgages: Loss Distribution (OFHEO Working Papers); Calem, P., & LaCour-Little, M., 2004. Risk-based Capital Requirements for Mortgage Loans (Journal of Banking & Finance), 28, 647-672; Qi, M., & Yang, X., 2009. Loss Given Default of High Loan-to-Value Residential Mortgages (Journal of Banking & Finance), 33, 788-799; Siemsen, T., & Vilsmeier, J., 2017. A Stress Test Framework for the German Residential Mortgage Market – Methodology and Application (Deutsche Bundesbank Discussion Paper).
[91] *See* Qi, M., & Yang, X., 2009. Loss Given Default of High Loan-to-Value Residential Mortgages (Journal of Banking & Finance), 33, 788-799; Georgescu, O., & Martin, D., 2021. Do Macroprudential Measures Increase Inequity? Evidence from the Euro Area Household Survey (European Central Bank Working Paper Series).

value of a property is calculated as the product of the property's initial value and the ratio of the real estate price indices between the initial period and the current period.[92]

Repeat-sales regression, which was first proposed by Bailey, Muth, and Nourse (1963), is a commonly used method for estimating real estate price indices.[93] Modern home price indices are commonly estimated using adaptations of the repeat-sale methodology.

While the values of individual properties generally follow the market trend, properties with defaulted loans (for example, foreclosed homes and REOs) are often sold at a deep discount. This is driven by: (1) negative information about the intrinsic value of the property and the industry, and (2) the sellers' (lenders') urgency to sell (likely at a suboptimal time) due to regulation and/or liquidity constraints.[94] Even though distressed sales often coincide with market downturns when buyers are likely to have limited resources, property-specific negative information together with the urgency to sell generate additional downward pressure on property prices. This implies that it is necessary to account for the distressed-sales discount when updating the LTV ratio of a defaulted loan.

Research has shown that property owners with high LTV ratios (low equity) are more willing to wait for the highest and best price.[95] This concept carries over to repossessions, where

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[92] *See* Pennington-Cross, A., 2003. Subprime & Prime Mortgages: Loss Distribution (OFHEO Working Papers); Bogin, A., Doerner, W., & Larson, W., 2016. Missing the Mark: House Price Index Accuracy and Mortgage Credit Modeling (Federal Housing Finance Agency Working Paper Series); Siemsen, T., & Vilsmeier, J., 2017. A Stress Test Framework for the German Residential Mortgage Market – Methodology and Application (Deutsche Bundesbank Discussion Paper).

[93] *See* Bailey, M., Muth, R., & Nourse, H., 1963. A Regression Method for Real Estate Price Index Construction (Journal of the American Statistical Association), 58:304, 933-942.

[94] *See* Shleifer, A., & Vishy, R., 1992. Liquidation Values and Debt Capacity: A Market Equilibrium Approach (The Journal of Finance), 47:4, 1343-1366; Clauretie, T., & Daneshvary, N., 2009. Estimating the House Foreclosure Discount Corrected for Spatial Price Interdependence and Endogeneity of Marketing Time (Real Estate Economics), V37:1, 43-67; Campbell, J., Giglio, S., & Pathak, P., 2011. Forced Sales and House Prices (American Economic Review), 101, 2108-2131; Chu, Y., 2016. Asset Fire Sales by Banks: Evidence from Commercial REO Sales.; Ramcharan, R., 2020. Bank's Balance Sheets and Liquidation Values: Evidence from Real Estate Collateral.

[95] *See* Genesove, D., & Mayer, C., 1997. Equity and Time to Sale in the Real Estate Market (The American Economic Review), 87:3, 255-269.

banks in possession of distressed properties with high LTV ratios are more willing to wait for the highest and best price.[96] On the other hand, borrowers with low LTV ratios (high equity) are less likely to end up in distress. Distress for such loans is driven by special circumstances, for example, when the borrower has information that the property is in bad condition and unlikely to sell for market value. This phenomenon leads to selection of low LTV ratio loans into distress.[97] That is, properties that enter distress with low LTV ratios at origination may have been initially overvalued. These dynamics are borne out in CRE transactions data for the hotel, retail, and office property types, that is, low LTV ratio (at origination) loans have a higher price decline between transactions (demonstrating a negative relationship between LTV ratio and price discount). Model performance for these property types is best when the distress flag is interacted with LTV ratio at origination across multiple dimensions (by LTV ratio decile, by loan size decile, and by year of default).

Alternative approaches

The Board considered multiple alternative approaches before choosing the current model specification for the LGD model sub-component. The process included the exploration of different alternatives for all model terms, as described below.

The Board considered using a hedonic pricing model to estimate the discount factor, rather than the modified standard repeat-sales regression framework currently used. The hedonic regression method involves estimating the price of an individual property as a function of its characteristics, such as building age, square feet, number of floors, number of units, buyer type,

[96] *See* Leow, M., & Mues, C., 2012. Predicting Loss Given Default (LGD) for Residential Mortgage Loans: A Two-stage Model and Empirical Evidence for UK Bank Data (International Journal of Forecasting) 28, 183-195.
[97] *See* Leow, M., & Mues, C., 2012.

seller type, and property location.[98] Estimating real estate price indices using the repeat-sales method is less data intensive than the hedonic approach. In addition, unlike the hedonic model, because the dependent variable in the repeat-sales regression is the log price return between sales of the same property, there is no need for additional information on property characteristics. Ultimately, the Board chose the repeat-sales approach, as it is more parsimonious. Estimating an accurate hedonic regression model requires many more property-specific characteristics than are available from Schedule H.2. In addition, the Board's analysis shows that model performance for the repeat sales model is strong.

The Board chose to use the U.S. CRE price index—the aggregate index published in the scenario—but considered using an alternative price index to update property valuations from the time of origination to the exercise date: more granular, market- and property-type level indices provided by a third-party data vendor. These indices differ structurally in that the aggregate published index is based on observed transaction data, while the more granular indices are based on data collected on property NOIs and investor-reported capitalization rates. These structural differences lead to very different behavior across the indices during the 2008 financial crisis and the COVID-19 pandemic. The aggregate published index declined more precipitously in the 2008 financial crisis than did the more granular indices. Capitalization rates continued to compress (decline) in 2007–08, causing the more granular indices to diverge from the declining realized transaction prices. As a result, using the U.S. CRE price index in the model leads to better performance in the back-testing sample than the more granular indices, particularly for loans with low LTV ratios (where the distribution of Schedule H.2 loans is concentrated).

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98 *See* Gatzlaff, D., & Holmes, C., 2013. Estimating Transaction-Based Price Indices of Local Commercial Real Estate Markets Using Public Assessment Data (Journal of Real Estate Finance and Economics), 46, 260-281.

The Board also considered modeling LGD directly in a reduced-form regression framework but found that the structural approach performed at least as well as reduced-form alternatives, is simpler with results that are more straightforward to interpret and limits external dependencies and assumptions.

(3) Data and Data Adjustments

Data Sources

The main data source used to estimate the repeat-sales regression framework specified in Equation B8 is a database of CRE transactions provided by a third-party data vendor. The database contains various transactions, property, and financing characteristics for nationwide sales and refinancings of at least $2.5 million, starting from January 2001. Among the set of information included at the transaction level are sales price; seller, buyer, and lender characteristics; and additional loan information. Critically, the data also includes an indicator identifying whether the transaction resolves distressed debt. The presence of this indicator supports the identification and estimation of the average price discount on properties sold to resolved distressed loans ($\hat{\beta}_d$ in Equation B8, and in turn the discount factor $\widehat{DF}_p$).

Data Adjustments

The Board implements several data filtering and adjustment steps to the source data provided by the third-party data vendor to construct the repeat-sales sample that is used to estimate Equation B7. Only transactions that are classified as sales financed by a bank loan are included in the estimation of the discount factor; other transaction types (for example, entity level, refinance) and financing types (for example, CMBS) are discarded. The Board then applies a set of additional filters to ensure the soundness of the final estimation sample. Records that meet any of the following criteria are discarded:

- The holding period—the time gap between the first and second sales—is less than four quarters. Such a short gap between sales is potentially indicative of exceptional circumstances; the observed price change could be reflective of changes in circumstance that violate the assumptions of the repeat sales model.
- The sales price is zero or negative. Such observations are likely mis-measured or do not represent arms-length transactions.
- Square footage changed by more than 10 percent between the first and second sales. These observations are likely reflective of a physical change to the property that is sufficient to warrant the two sales incomparable.
- The repeat-sales pair is associated with sales of portfolios with multiple properties. When properties are aggregated, the allocation of prices across individual properties in the portfolio may not be reflective of the individual market value.
- The first sale price in each pair is less than $2.5 million (the minimum price threshold stated by the data provider).
- The year built indicated for the property in the second sale is after the year built indicated for the property in the first sale. If this is the case, the first sale is likely to be the land acquisition cost and thus the two properties are not comparable in terms of property type.
- The sale prices changed by more than 50 percent annually. Such extreme observations are possible data errors and have undue influence on model estimates.

After applying the above data treatments, the time period for the final estimation sample ranges from 2002–2021. This period contains approximately 24,000 repeat-sales pairs, 12 percent of which are reported as sales that resolved distressed debt.

The CRE price index used to compute the term $\left(\frac{ScenarioCREPrice_t}{HistoricalCREPrice_{t=orig}}\right)$ in Equation B6 is the U.S. Commercial Real Estate Price Index published in the Board's stress test scenario disclosure.

These adjustments are implemented to ensure that the estimation sample is representative of the Schedule H.2 data used for model projections, that model coefficients are estimated accurately and with precision, and that the resulting fit of the model is not unnecessarily hindered due to mis-reported data and/or outlier observations.

(4) Assumptions and Limitations

The CRE LGD model makes several assumptions:

- The LTV ratio at default is equivalent to the LTV ratio at liquidation, that is, there is no change in valuation between the time of default and the time of liquidation. Additionally, the Board assumes that liquidation expenses and carrying costs are zero. Analysis shows that LGD is not correlated with time-to-liquidation, and that the LGD model performs well across the distribution of time-to-liquidation.
- The values of individual properties follow the general market trend captured by the U.S. CRE price index. The Board explored and regularly monitors the implications of using more granular price indices in the model. The usage of more granular indices does not offer a clear improvement over the chosen model. Accordingly, the Board chose the simplest option to conform with the principles of supervisory stress testing.
- Properties sold to resolve distressed loans are sold at a discount. The Board's analysis of available CRE transaction data shows clear evidence of the existence of a discount factor. Removing the discount factor from the LGD model subcomponent significantly hinders model performance, resulting in an underprediction of LGD.
- The price discount associated with distressed sales is constant throughout the stress horizon. The Board explored regression specifications that allow the discount factor to vary with macroeconomic conditions, but did not find a statistically significant relationship, supporting the assumption of a constant price discount.

(5) Questions

Question B6: The Board seeks comment on the alternative approach of a reduced-form regression model to directly model LGD as compared to its current approach of exploiting the structural relationship between current LTV and LGD.

Question B7: The Board seeks comment on additional factors that should be considered in the LGD model as compared to the set of factors currently included in the Board's specification.

Question B8: The Board seeks comment on its use of a single, aggregate price index to update collateral value to project LGD, as compared to the alternative of using price indices at other levels of granularity.

Question B9: The Board seeks comment on the current property type segmentation of the model used to estimate the discount factor, as compared to an alternative of a pooled model or a model segmented on another dimension.

Question B10: The Board seeks comment on the alternative of using a discount factor that is time-varying and/or depends on market conditions, as compared to the Board's current approach of using a constant discount factor.

c. EAD Sub-Component

The exposure at default (EAD) model sub-component assumes EAD for CRE loans equals the total committed exposure amount, which is the outstanding balance of the loan plus any remaining undrawn committed amount at the start of the projection horizon.

(1) Model Specification

The Exposure at Default (EAD) model sub-component assigns $EAD_{i,t}$ for each loan i and each quarter t throughout the projection horizon based on a series of assumptions. The primary starting assumption is that, for both construction and income-producing loans, EAD is equal to the committed balance of the loan as of the reporting date for the given stress test event (t_0):

Equation B10 – EAD

$$EAD_{i,t} = CommittedBalance_{i,t_0}$$

Starting EAD is then adjusted through the projection horizon based on several additional assumptions:

- The Board assumes that losses are realized contemporaneously (that is, projected $EL_{i,t}$ is realized in quarter t). Loan balances are dynamically adjusted to account for the portion of the original loan that survives to quarter t based on the modeled default in prior quarters $\{\widehat{PD}_{i,t=1}, \ldots, \widehat{PD}_{i,t-1}\}$, that is, survival adjustment.
- For loans that mature within the projection horizon, the Board assumes full payoff, that is, no loan is extended into quarters past its reported maturity date. In the quarter following maturity of the loan, the loan is replaced with a "new" loan with similar characteristics. See Section B.ii.c.(2) for further discussion of this assumption. Specifically, the "new" loan is assumed to enter the portfolio with the following characteristics:
  - Committed balance equal to the balance observed at the time of origination of the original loan.

- Static characteristics that match the original loan (for example, property type, location).
- Dynamic characteristics that are equal to the average across all loans within the same property type and location in quarter t.
- A maturity date equal to the greater of 13 quarters into the future or the average original term for all recently originated loans of a given type (income-producing or construction) at the same firm, where available.
- Portfolio-level EAD follows the path of firm-portfolio-level balances provided exogenously to the model.

First, starting EAD is adjusted to ensure that the sum of loan-level EAD_{i,t_0} matches the firm-portfolio-level balances path provided exogenously to the CRE model (see Section A of Aggregation). The Board applies a scaling factor based on the sum of Schedule H.2 reported outstanding balances across all loans within each firm and portfolio.

The Board then implements several recursive steps to generate quarterly projections of loan-level balances ($EAD_{i,t}$) for all loans that are not considered to be in default at start of the projection horizon.[99] These steps account for probabilistic default (that is, survival adjustment) and maturity behavior, and ultimately ensure that firm-portfolio-level balances reconcile to the exogenous balance path.

Equation B11 – Survival-Adjusted EAD

$$EAD\_adj_{i,t} = \begin{cases} EAD_{i,t} \ if \ t = 0 \\ OriginationBalance_i \ if \ t = \text{maturity date for loan } i \\ \left(1 - \widehat{PD}_{i,t}\right) * EAD_{i,t-1} \text{ otherwise} \end{cases}$$

After the loan-level adjustments in Equation B11 are applied for the entire projection horizon, a scaling factor is applied to ensure the total balance growth of each firm portfolio is consistent with the exogenously provided balance path:

[99] As described above, loans that are reported at least 90 days past due, placed on non-accrual status, or extended with a rating equivalent to CCC or below are considered in default. EAD for such loans is held constant at the starting level through the projection horizon. The method to account for losses from such loans is explained further in section B.ii.e.

Equation B12 – Model-Projected EAD

$$\widehat{EAD}_{i,t} = EAD\_adj_{i,t} * \frac{bal\_growth_{f,y,t}}{ead\_growth_{f,y,t}}$$

where $bal\_growth_{f,y,t}$ is the quarterly growth rate of total balances of the firm f and portfolio y that loan i is categorized within—as specified by the exogenously provided firm-portfolio-level balances path—and $ead\_growth_{f,y,t}$ is the quarterly growth rate implied by the sum of $EAD\_adj_{i,t}$ for all surviving loans i within firm f and portfolio y.

(2) Rationale

The Board believes that the assumption-based approach to modeling EAD (outlined in the prior section) is the best option as it is independent (developed internally), consistent (applies equally to all covered firms), simple (straightforward to interpret), robust and stable, and conservative.

Assumption of full draw

The Board assumes that EAD is equal to the fully committed balance of the loan rather than, for example, employing a statistical model to project EAD. This assumption applies to both construction and income-producing loans for the reasons described below.

Construction loans are usually project-specific in that the borrower and the firm negotiate loan terms to address the requirements of a specific development project. At the beginning of the life of each facility, the utilized balance of the facility is zero and the borrower draws additional funding over time. Construction loans, however, generally share a common structure in that the total commitment amount of the loan is based on the total projected construction budget (including interest reserves, hard and soft construction costs, and other costs). The borrower is expected to fully draw down the original commitment amount to finish the project.

Given that construction loans typically have short terms, the Board makes the simplifying assumption that EAD on construction loans is equivalent to the full commitment amount. Test results from various ordinary least squares and Tobit[100] models for the EAD of construction loans, including macroeconomic drivers, CRE market conditions, and loan-specific characteristics as independent variables, provide empirical evidence that construction loans are often fully drawn at default in a stressed macroeconomic environment.

Most income-producing loans are drawn fully at origination, partially amortize over the loan term, and have a large balloon payment due at maturity. In these cases, the EAD estimation exercise is trivial. The commitment amount equals the utilized (outstanding) balance of the loan, and the utilization rate, by design, is 100 percent.

In certain cases, the borrower might be a real estate investor who is actively managing a portfolio of real estate properties. In these cases, the firm and borrower often arrange a fully secured contingent line of credit. The purpose of the line of credit is to ensure that the borrower has the flexibility to use the funds to acquire new properties or make improvements to existing properties. In a typical case, a borrower would use the line of credit to acquire a new property, using the equity in an existing portfolio of properties as collateral. After the purchase, the borrower and firm would typically make a separate, project-specific loan to finance the newly acquired property, and by doing so repay the revolving facility.

As noted, these facilities are typically negotiated in advance and fully secured by liens on existing properties. Accordingly, in certain cases on Schedule H.2, income-producing loans are observed with committed balances exceeding the outstanding balance. From an EAD

[100] Tobit regression is used to model a dependent variable that is censored in some fashion, i.e., values above or below the censoring threshold are equal to the threshold value. EAD, for example, is censored below at zero percent and above at 100 percent.

perspective, the Board makes the conservative and simplifying assumption that the borrower fully draws the loan available to them. As of 2024Q4, income-producing loans were 96 percent utilized, in aggregate.

Replacement of maturing loans

The Board assumes that maturing loans are replaced with a loan of similar characteristics in the quarter following the reported maturity date. This approach simulates the industry practice of re-financing the balloon payment of a maturing CRE loan into a new loan. The Board makes the simplifying assumption that the terms and conditions of the re-financed loan are roughly the same as the original loan.

Among the alternative approaches considered is to instead assume a static portfolio. This approach would account for the seasoning of loans, and ultimately maturity, but would not replace them with “new” loans. The main benefit of this alternative relative to the chosen approach is simplicity in that it would eliminate the need for any assumptions about replacement loans. One drawback to this approach, however, is that the maturity profile of a specific portfolio may result in a distribution of loans in the projection horizon that is of a substantially different risk profile than what is observed as of the exercise date. For example, consider a firm whose portfolio comprises 50 percent construction loans with 1-year maturities, and 50 percent income-producing loans with 5-year maturities. In a static portfolio approach, the construction loans would mature after four quarters. From the fifth quarter forward, the firm’s portfolio would be assumed to include only 100 percent income-producing loans, a very different business model than observed at the beginning of the projection horizon.

A second alternative approach would hold the age and maturity profile of each portfolio constant at their starting values. The implication in this approach is that loans do not age and mature over the projection horizon, while other time-varying risk factors evolve. The key benefit of this approach is simplicity, with no need to make assumptions about the replacement of maturing loans. Unlike the static portfolio approach, it would hold the current portfolio composition constant, approximating a constant business strategy. This approach, however, ignores loan-specific maturity risk and its interaction with the macroeconomic scenario, a key driver of loan distress in the PD model specification.

The selected approach has the benefit of maintaining consistency in the firm's portfolio composition while directly accounting for the maturity profile of the individual loans. This approach achieves a balance of simplicity, flexibility, and accuracy, which led the Board to choose it among alternatives.

Balance path reconciliation

The Board reconciles loan-level balance with the exogenous, firm-portfolio-level balance path by adjusting the balances of existing loans rather than, for example, creating additional synthetic loans to match any discrepancies. This approach ensures that the portfolio composition remains somewhat consistent through the projection horizon. The main driver of changes in risk profile over the projection horizon is modeled PD, that is, loans with higher PD will have balances adjusted downwards more quickly than those with lower PD (see Equation B11). In addition, the chosen approach is flexible enough to accommodate negative, flat, or positive balance growth (while a synthetic loan approach would not be).

(3) Data and Data Adjustments

There is no additional statistical model, and thus no coefficients or parameters to be calibrated from data, in the CRE EAD model sub-component. The EAD model is implemented on loans reported on Schedule H.2 as of the exercise date. Please see Section B.ii.e for more detail on the projection of results.

(4) Assumptions and Limitations

The main assumptions of the CRE EAD model sub-component are as follows. The Board believes these assumptions are appropriate for the reasons described in section B.ii.c.(2).

- The EAD of CRE loans equals the total committed exposure amount, which is the outstanding balance of the loan plus any remaining undrawn committed amount at the start of the projection horizon.
- Maturing loans will be replaced in the portfolio with a loan in the same location, backed by the same static property type characteristics, with an LTV ratio updated to reflect projected market conditions.
- The replacement loan's maturity term is the simple average of original maturity terms across all other recently originated loans within the same bank and loan type (income-producing or construction).
- The impact of a given loan on portfolio balances is adjusted for the loan's probabilistic survival.

Some of the limitations of the modeling approach used in the CRE EAD model sub-component are:

- The EAD model is not sensitive to the macroeconomic scenario. As mentioned above, the Board believes the full draw assumption to be appropriate regardless of scenario.
- The EAD model does not allow for different draw behavior across construction loans that are not fully utilized. While data is scarce, empirical analysis conducted by the Board shows that construction loans are often fully drawn at default in a stressed macroeconomic environment.

(5) Questions

Question B11:

The Board seeks comment on the alternative of using a statistical model, as compared to the Board's current assumption-driven approach to model EAD.

Question B12:

The Board seeks comment on additional factors that should be considered in the EAD model as compared to the set of factors currently included in the Board's specification.

d. Auxiliary Model Sub-Component

(1) Model Specification

The CRE auxiliary scenario model sub-component extends the Board's published stress test scenario to produce hypothetical scenario values for three variables capturing CRE market fundamentals that are included in the PD model sub-component: CRE price index, CRE rent index, and vacancy rate. A third-party data vendor provides historical values for these three variables differentiated by market and property type (retail, industrial, hotel, multi-family, and office). The inclusion of these three variables in the PD model provides information on CRE-specific market conditions that are key drivers of loan default but are not contained in the set of macroeconomic variables published in the Board's stress test scenario disclosure. Academic literature has shown that local market conditions are important predictors of loan default.[101] The CRE auxiliary scenario model sub-component is necessary to project these variables over the projection horizon.

Projections for these variables are generated from a set of 15 linear regressions (the combination of three variables and five property types); data is pooled across all markets within each property type to estimate the regressions. The general form is an autoregressive distributed lag (ARDL) model,[102] where independent variables differ across property types:

Equation B13 – General Regression Specification for CRE Auxiliary Scenario Variables

$$\Delta LocIndex_{m,p,t} = \alpha_p + \sum_{j=1}^{J} \beta_{p,j} \Delta LocIndex_{m,p,t-j} + \sum_{k=0}^{K} \gamma_{p,k} \Delta Macro_{t-k} + \varepsilon_{m,p,t}$$

[101] *See* An, X., Deng, Y., Nichols, J., & Saunders, A., 2013. Local Traits and Securitized Commercial Mortgage Defaults, (Journal of Real Estate Finance & Economics) 47, 787-813.

[102] ARDL models feature lagged values of the dependent variable as well as lagged values of the independent (exogenous) variable(s).

where $LocIndex_{m,p,t}$ represents rent, vacancy, and price indices in local market m for property type p at time t, and $Macro$ represents macroeconomic variable(s) provided in the Board's stress test scenario disclosure. Note that parameters are pooled across markets within a property type, i.e., $\beta_{m,p,j} = \beta_{p,j}; \gamma_{m,p,k} = \gamma_{p,k}$.

The macroeconomic variables vary across the 15 regressions but include changes in the aggregate unemployment rate, changes in the aggregate CRE price index, changes in state-level house price indices, and the level of the BBB spread. In addition to macroeconomic variables, an autoregressive structure is included in each regression, i.e., values of the dependent variable from one and two quarters prior are included as independent variables.

The regressions are estimated using historical data provided by the third-party data vendor. As a first step, the Board seasonally adjusts each time series provided by the vendor using the X11 procedure. Coefficient estimates ($\hat{\beta}_{p,j}, \hat{\gamma}_{p,k}$) are obtained via ordinary least squares regression. The resulting coefficient estimates, for each of the 15 regressions, are displayed in Tables B5, B6, and B7.

Table B5 - Regression results for the rent index equations in the CRE auxiliary scenario model sub-component.

Variable	Transformation	Source	Estimate	Standard Error
Hotel Regression				
Constant			0.005	0.0004
CRE Rent Index from the Previous Quarter	Market and property-type-level CRE rent index, expressed as quarter-over-quarter natural log change and lagged by one quarter	Third-party data vendor	-0.263	0.015

Variable	Transformation	Source	Estimate	Standard Error
CRE Rent Index from Two Quarters Prior	Market and property-type-level CRE rent index, expressed as quarter-over-quarter natural log change and lagged by two quarters	Third-party data vendor	-0.015	0.015
Unemployment Rate	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change	Board Stress Test Scenario	-0.022	0.002
Unemployment Rate from the Previous Quarter	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change and lagged by one quarter	Board Stress Test Scenario	-0.017	0.002
Unemployment Rate from Two Quarters Prior	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change and lagged by two quarters	Board Stress Test Scenario	-0.007	0.002
Industrial Regression				
Constant			0.004	0.001
CRE Rent Index from the Previous Quarter	Market and property-type-level CRE rent index, expressed as quarter-over-quarter natural log change and lagged by one quarter	Third-party data vendor	0.359	0.011
CRE Rent Index from Two Quarters Prior	Market and property-type-level CRE rent index, expressed as quarter-over-quarter natural log change and lagged by two quarters	Third-party data vendor	0.072	0.010
Unemployment Rate from the Previous Quarter	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change and lagged by one quarter	Board Stress Test Scenario	-0.003	0.001
Unemployment Rate from Two Quarters Prior	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change and lagged by two quarters	Board Stress Test Scenario	-0.007	0.001

Variable	Transformation	Source	Estimate	Standard Error
House Price Index from the Previous Quarter	State-level house price index, expressed as quarter-over-quarter natural log change and lagged by one quarter	Board Stress Test Scenario	0.101	0.014
BBB Spread	Difference between U.S. BBB corporate bond yield and the U.S. 10-year treasury rate	Board Stress Test Scenario	-0.001	0.0004
Multi-Family Regression				
Constant			0.003	0.0002
CRE Rent Index from the Previous Quarter	Market and property-type-level CRE rent index, expressed as quarter-over-quarter natural log change and lagged by one quarter	Third-party data vendor	0.232	0.012
CRE Rent Index from Two Quarters Prior	Market and property-type-level CRE rent index, expressed as quarter-over-quarter natural log change and lagged by two quarters	Third-party data vendor	0.153	0.012
Unemployment Rate from the Previous Quarter	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change and lagged by one quarter	Board Stress Test Scenario	-0.009	0.001
Unemployment Rate from Two Quarters Prior	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change and lagged by two quarters	Board Stress Test Scenario	-0.001	0.001
House Price Index from the Previous Quarter	State-level house price index, expressed as quarter-over-quarter natural log change and lagged by one quarter	Board Stress Test Scenario	0.046	0.009
Mortgage Rate	U.S. mortgage rate, expressed as quarter-over-quarter percentage point change	Board Stress Test Scenario	0.001	0.001
Office Regression				
Constant			0.005	0.001

Variable	Transformation	Source	Estimate	Standard Error
CRE Rent Index from the Previous Quarter	Market and property-type-level CRE rent index, expressed as quarter-over-quarter natural log change and lagged by one quarter	Third-party data vendor	0.408	0.010
CRE Rent Index from Two Quarters Prior	Market and property-type-level CRE rent index, expressed as quarter-over-quarter natural log change and lagged by two quarters	Third-party data vendor	-0.067	0.010
Unemployment Rate from the Previous Quarter	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change and lagged by one quarter	Board Stress Test Scenario	-0.007	0.001
Unemployment Rate from Two Quarters Prior	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change and lagged by two quarters	Board Stress Test Scenario	-0.003	0.001
BBB Spread	Difference between U.S. BBB corporate bond yield and the U.S. 10-year treasury rate	Board Stress Test Scenario	-0.001	0.0004
Retail Regression				
Constant			0.001	0.0003
CRE Rent Index from the Previous Quarter	Market and property-type-level CRE rent index, expressed as quarter-over-quarter natural log change and lagged by one quarter	Third-party data vendor	0.795	0.012
CRE Rent Index from Two Quarters Prior	Market and property-type-level CRE rent index, expressed as quarter-over-quarter natural log change and lagged by two quarters	Third-party data vendor	-0.023	0.011
Unemployment Rate from the Previous Quarter	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change and lagged by one quarter	Board Stress Test Scenario	-0.0003	0.001

Variable	Transformation	Source	Estimate	Standard Error
Unemployment Rate from Two Quarters Prior	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change and lagged by two quarters	Board Stress Test Scenario	-0.001	0.0005
House Price Index from the Previous Quarter	State-level house price index, expressed as quarter-over-quarter natural log change and lagged by one quarter	Auxiliary Translation of Board Stress Test Scenario	0.014	0.010
House Price Index from Two Quarters Prior	State-level house price index, expressed as quarter-over-quarter natural log change and lagged by two quarters	Auxiliary Translation of Board Stress Test Scenario	0.028	0.011
BBB Spread	Difference between U.S. BBB corporate bond yield and the U.S. 10-year Treasury rate	Board Stress Test Scenario	-0.001	0.0001

Table B6 - Regression results for the vacancy rate equations in the CRE auxiliary scenario model sub-component.

Variable	**Transformation**	**Source**	**Estimate**	**Standard Error**
Hotel Regression				
Vacancy Rate from the Previous Quarter	Market and property-type-level vacancy rate, expressed as quarter-over-quarter percentage point change and lagged by one quarter	Third-party data vendor	-0.161	0.016
Vacancy Rate from Two Quarters Prior	Market and property-type-level vacancy rate, expressed as quarter-over-quarter percentage point change and lagged by two quarters	Third-party data vendor	-0.071	0.016
Unemployment Rate	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change	Board Stress Test Scenario	2.572	0.130
Unemployment Rate from the Previous Quarter	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change and lagged by one quarter	Board Stress Test Scenario	-0.703	0.129
Industrial Regression				
Vacancy Rate from the Previous Quarter	Market and property-type-level vacancy rate, expressed as quarter-over-quarter percentage point change and lagged by one quarter	Third-party data vendor	0.077	0.011
Vacancy Rate from Two Quarters Prior	Market and property-type-level vacancy rate, expressed as quarter-over-quarter percentage point change and lagged by two quarters	Third-party data vendor	0.068	0.011
Unemployment Rate	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change	Board Stress Test Scenario	0.331	0.039

Variable	Transformation	Source	Estimate	Standard Error
Unemployment Rate from the Previous Quarter	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change and lagged by one quarter	Board Stress Test Scenario	0.179	0.045
Unemployment Rate from Two Quarters Prior	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change and lagged by two quarters	Board Stress Test Scenario	0.162	0.039
Multi-Family Regression				
Vacancy Rate from the Previous Quarter	Market and property-type-level vacancy rate, expressed as quarter-over-quarter percentage point change and lagged by one quarter	Third-party data vendor	-0.266	0.012
Vacancy Rate from Two Quarters Prior	Market and property-type-level vacancy rate, expressed as quarter-over-quarter percentage point change and lagged by two quarters	Third-party data vendor	-0.079	0.012
Unemployment Rate	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change	Board Stress Test Scenario	0.459	0.049
Unemployment Rate from the Previous Quarter	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change and lagged by one quarter	Board Stress Test Scenario	0.114	0.049
Office Regression				
Vacancy Rate from the Previous Quarter	Market and property-type-level vacancy rate, expressed as quarter-over-quarter percentage point change and lagged by one quarter	Third-party data vendor	0.156	0.010
Vacancy Rate from Two Quarters Prior	Market and property-type-level vacancy rate,	Third-party data vendor	0.200	0.010

Variable	Transformation	Source	Estimate	Standard Error
	expressed as quarter-over-quarter percentage point change and lagged by two quarters			
Unemployment Rate	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change	Board Stress Test Scenario	0.193	0.042
Unemployment Rate from the Previous Quarter	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change and lagged by one quarter	Board Stress Test Scenario	0.331	0.042
BBB Spread	Difference between U.S. BBB corporate bond yield and the U.S. 10-year treasury rate	Board Stress Test Scenario	0.017	0.005
Retail Regression				
Vacancy Rate from the Previous Quarter	Market and property-type-level vacancy rate, expressed as quarter-over-quarter percentage point change and lagged by one quarter	Third-party data vendor	0.222	0.011
Vacancy Rate from Two Quarters Prior	Market and property-type-level vacancy rate, expressed as quarter-over-quarter percentage point change and lagged by two quarters	Third-party data vendor	0.064	0.011
Unemployment Rate	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change	Board Stress Test Scenario	0.190	0.027
Unemployment Rate from the Previous Quarter	U.S. unemployment rate, expressed as quarter-over-quarter percentage point change and lagged by one quarter	Board Stress Test Scenario	0.142	0.026
BBB Spread	Difference between U.S. BBB corporate	Board Stress Test Scenario	0.011	0.003

Variable	Transformation	Source	Estimate	Standard Error
	bond yield and the U.S. 10-year Treasury rate			
House Price Index	State-level house price index, expressed as quarter-over-quarter natural log change	Auxiliary Translation of Board Stress Test Scenario	-2.548	0.296

Table B7 - Regression results for the price index equations in the CRE auxiliary scenario model sub-component.

Variable	Transformation	Source	Estimate	Standard Error
Hotel Regression				
Constant			-0.002	0.0004
CRE Price Index from the Previous Quarter	Market and property-type-level CRE price index, expressed as quarter-over-quarter natural log change and lagged by one quarter	Third-party data vendor	0.399	0.015
CRE Price Index from Two Quarters Prior	Market and property-type-level CRE price index, expressed as quarter-over-quarter natural log change and lagged by two quarters	Third-party data vendor	-0.033	0.013
Aggregate CRE Price Index	Property-level, aggregate CRE price index, expressed as quarter-over-quarter natural log change	Third-party data vendor	0.651	0.014
Industrial Regression				
Constant			-0.0002	0.0003
CRE Price Index from the Previous Quarter	Market and property-type-level CRE price index, expressed as quarter-over-quarter natural log change and lagged by one quarter	Third-party data vendor	0.463	0.013
CRE Price Index from Two Quarters Prior	Market and property-type-level CRE price index, expressed as quarter-over-quarter natural log change and lagged by two quarters	Third-party data vendor	0.088	0.012
Aggregate CRE Price Index	Property-level, aggregate CRE price index, expressed as quarter-over-quarter natural log change	Third-party data vendor	0.455	0.018
Multi-Family Regression				

Variable	Transformation	Source	Estimate	Standard Error
Constant			0.001	0.0002
CRE Price Index from the Previous Quarter	Market and property-type-level CRE price index, expressed as quarter-over-quarter natural log change and lagged by one quarter	Third-party data vendor	0.640	0.012
CRE Price Index from Two Quarters Prior	Market and property-type-level CRE price index, expressed as quarter-over-quarter natural log change and lagged by two quarters	Third-party data vendor	-0.062	0.011
Aggregate CRE Price Index	Property-level, aggregate CRE price index, expressed as quarter-over-quarter natural log change	Third-party data vendor	0.323	0.009
Office Regression				
Constant			-0.0003	0.0002
CRE Price Index from the Previous Quarter	Market and property-type-level CRE price index, expressed as quarter-over-quarter natural log change and lagged by one quarter	Third-party data vendor	0.572	0.012
CRE Price Index from Two Quarters Prior	Market and property-type-level CRE price index, expressed as quarter-over-quarter natural log change and lagged by two quarters	Third-party data vendor	-0.006	0.011
Aggregate CRE Price Index	Property-level, aggregate CRE price index, expressed as quarter-over-quarter natural log change	Third-party data vendor	0.359	0.011
Retail Regression				
Constant			-0.0004	0.0002
CRE Price Index from the Previous Quarter	Market and property-type-level CRE price index, expressed as quarter-over-quarter	Third-party data vendor	0.467	0.013

Variable	Transformation	Source	Estimate	Standard Error
	natural log change and lagged by one quarter			
CRE Price Index from Two Quarters Prior	market and property-type-level CRE price index, expressed as quarter-over-quarter natural log change and lagged by two quarters	Third-party data vendor	0.001	0.012
Aggregate CRE Price Index	Property-level, aggregate CRE price index, expressed as quarter-over-quarter natural log change	Third-party data vendor	0.536	0.016

The Board proceeds with the below steps to project each of the three variables (CRE rent index, vacancy rate, and CRE price index) under the hypothetical scenario, by market and property type.

First, the Board produces aggregate, national-level[103] projections for each property type using the estimated coefficients from Tables B5 – B7 and the hypothetical scenario values of independent variables from the Board's published stress test scenario:[104]

Equation B14 – Model-Projected Changes in Aggregate Index

$$\Delta \widehat{AggIndex}_{p,t} = \hat{\alpha}_p + \sum_{j=1}^{J} \hat{\beta}_{p,j} \Delta \widehat{AggIndex}_{p,t-j} + \sum_{k=0}^{K} \hat{\gamma}_{p,k} \Delta Macro_{t-k}$$

The result of Equation B14 is 15 quarterly time series of projected changes (one for each of the three variables and five property types) that extends for the length of the projection horizon ($\Delta \widehat{AggIndex}_{p,t}$).

[103] A third-party data vendor provides an aggregate time series for each property type that is based on the stock-weighted average across all U.S. markets.
[104] The U.S. Commercial Real Estate Price Index series in the Board's stress test scenario is used to project aggregate price indices for all property types.

Projected changes in the aggregate index are then applied uniformly to each market's starting point level. For CRE rent and price indices, the aggregate changes are applied in percentage change form (Equation B15), while aggregate vacancy rate changes are applied in absolute terms (Equation B16).

Equation B15 – Model-Projected Changes in Local Rent and Price Indices

$$LocIndex_{m,p,t} = LocIndex_{m,p,t=0} \times \left(\frac{\widehat{AggIndex}_{p,t}}{\widehat{AggIndex}_{p,t=0}}\right)$$

Equation B16 – Model-Projected Changes in Local Vacancy Rates

$$LocIndex_{m,p,t} = LocIndex_{m,p,t=0} + (\widehat{AggIndex}_{p,t} - \widehat{AggIndex}_{p,t=0})^{105}$$

where $LocIndex_{m,p,t=0}$ is the market-specific starting point level as of the exercise date.

(2) Rationale

The CRE auxiliary scenario model sub-component seeks to address a limitation of the set of macroeconomic variables published in the Board's stress test scenario disclosure. As discussed in the CRE PD model sub-component section B.ii.a, loan default for CRE loans is driven by local market real estate conditions. The published set of macroeconomic variables does not contain a sufficient set of information to capture these risks; the only CRE-specific variable in the disclosure is the national aggregate commercial real estate price index. Other key metrics, such as vacancy rates and rents, are not provided.

The specification of the CRE auxiliary scenario model was determined based on the Board's policies and principles for model development. The principles of simplicity, robustness and stability[106] were ultimately applied to condense a choice set spanning multiple modeling approaches and macroeconomic variables. The choice of macroeconomic variables was

[105] Vacancy rate projections are bound at [0 percent, 100 percent].
[106] *See* Stress Testing Policy Statement.

informed by both economic theory and statistical selection procedures. Further discussion of the selection process and alternatives that were considered is provided below.

Alternative approaches

The Board considered many alternatives when selecting the ultimate model specification, including, but not limited to:

- Whether autoregressive (AR) terms should be included;
- Whether parameters should be pooled across markets;
- The choice of national or state-level macroeconomic variables;
- The use of principal components analysis (PCA) of the macroeconomic variables; and
- Whether a vector autoregressive (VAR) framework for local risk drivers outperforms simpler approaches.

The Board explored pooling coefficients by census division as well as allowing coefficients to vary across all markets (without pooling). The census division-level model offered forecasting improvements for some markets, but significant declines for others. Coefficients were unstable and/or unintuitive in some cases and these issues were only exacerbated when no pooling was applied. Previous academic literature has shown that rental market adjustment behavior may be similar across markets, and that cross-market correlations may be especially high during economic downturns.[107] In summary, model stability and forecast performance suggested that pooling by property type is the appropriate specification. Pooling by property type is also the most parsimonious option, as only fifteen rent, vacancy rate, and price regression equations are estimated in total. The pooled approach is simple and stable, allowing

[107] *See* Hendershott, P., Macgregor, B., & White., M., 2002. Explaining Real Commercial Rents Using an Error Correction Model with Panel Data (Journal of Real Estate Finance and Economics), 24:1/2, 59-87; Brouen, D., & Jennen, M., 2008. Local Office Rent Dynamics (Journal of Real Estate Finance & Economics), 39, 385-402; Hendershott, P., Jennen, M., & MacGregor, B., 2013. Modeling Space Market Dynamics: An Illustration Using Panel Data for US Retail (Journal of Real Estate Finance & Economics), 47, 659-687; Shilling, J., Sirmans, C.F., Slade, B., 2017. Spatial Correlation in Expected Returns in Commercial Real Estate Markets and the Role of Core Markets (Journal of Real Estate Finance & Economics), 54, 297-337.

for a straightforward interpretation of results, and minimizes bank-specific assumptions by reducing dispersion in geographic sensitivity to an aggregate macroeconomic shock.

In the CRE auxiliary scenario model, regressions are based on the first difference natural log transformation of rent index and price index, and the arithmetic first differences of vacancy rate. Constant terms are omitted from all vacancy rate regressions. First- and second-order autoregressive terms are included in each regression for price index, rent index, and vacancy rate. Out-of-sample forecasting exercises showed only small differences in performance between specifications with an autoregressive structure with two lags of the dependent variable—an AR(2) structure—and corresponding specifications without AR(2) terms for some property types, but the Board decided that models with autoregressive terms are preferable since residual autocorrelation in some of the property type regressions is eliminated by the introduction of the autoregressive structure. The minimal number of autoregressive terms, without sacrificing performance, was chosen in the interest of simplicity and consistency.

The macroeconomic variables and associated ARDL structure for each property type regression were chosen by balancing economic theory, parsimony, statistical significance, and out-of-sample forecasting performance. Up to two lags of the independent macroeconomic variables are included, i.e., the value of the macroeconomic variable from one or two quarters prior. Contemporaneous and first-lag changes in unemployment are included in all vacancy rate regressions, which have been shown in previous literature to respond more quickly to changes in economic conditions than rents. In the retail rent regression, only the second lag of change in unemployment is statistically significant. Despite this, the first lag is retained for model consistency. The finding of insignificant coefficients at shorter lags is in line with results in the academic literature, which shows that rents respond more slowly to changing economic conditions than vacancy rates.[108]

The specification in Table B7 is a pooled form of Equation B13, where parameters are constrained to be the same across markets within a property type and an AR(2) structure is included, analogous to the specification for rents and vacancy rates. The vendor-provided aggregate index is used as an independent variable in the regression. The Board also explored the forecasting performance of a model estimated on the U.S. CRE price index published in the Board's severely adverse scenario. Overall, performance was similar, but the performance of the model estimated on the vendor-provided aggregate index, was better during stress periods. When producing scenario projections following Equation B14, the U.S. CRE Price index published in the Stress Test scenario is used to project aggregate price indices for all property types.

In addition, a version of the model with an indicator variable for recession years interacted with the independent variables was tested. Scenario projections were slightly more severe when adding recession interactions, but the simpler model limits reliance on past outcomes by avoiding time-specific fixed effects. The chosen model performs as well as the more complex model in out-of-sample forecasting performance, sufficiently capturing the response of market-level price declines.

[108] *See* Wheaton, W., & Torto, R., 1994. Office Rent Indices and Their Behavior over Time (Journal of Urban Economics), 35, 121-139; Wheaton, W., Torto, R., & Evans, P., 1997. The Cyclic Behavior of the Greater London Office Market (Journal of Real Estate Finance & Economics), 15:1, 77-92.

(3) Data and Data Adjustments

A third-party data vendor provides source data for the three dependent variables in the CRE auxiliary scenario model sub-component: CRE price index, rent index, and vacancy rate by market and property type. Historical time series for these three variables are provided quarterly, separately for five property types: retail, industrial, hotel, multi-family, and office. The vendor also provides a national aggregate index for each of the three variables included in the model. The national aggregate is constructed as a weighted average across individual markets; weights are the size of the market as measured in square feet of the building stock. The Board first seasonally adjusts each of the time series provided by the vendor according to the X11 procedure.

Historical time series and hypothetical scenario values for the independent variables are obtained from the Board's stress test scenario. The two source datasets are joined based on the observation quarter and, in certain cases, geography (i.e., each market is mapped to a state to assign state-level HPI). Variable transformations (first differences, lags, and natural logarithms) are applied as outlined in Tables B5 – B7. These transformations are chosen to ensure stationarity of time series used in the model (i.e., with time-independent mean and variance). Stationarity is a key assumption of autoregressive models.

(4) Assumptions and Limitations

The main assumptions of the CRE auxiliary scenario model are:

- The property types provided by the third-party data vendor are representative of the property types of loans reported on Schedule H.2. Approximately 90 percent of Schedule H.2 loan balances as of 2024Q4 were reported in one of these five property types.
- The estimated sensitivity of local markets to an adverse aggregate macroeconomic shock is the same across markets within a given property type. Academic literature shows that this assumption has been borne out empirically in historical stressful conditions.[109]

[109] *See* Shilling, J., Sirmans, C.F., Slade, B., 2017. Spatial Correlation in Expected Returns in Commercial Real Estate Markets and the Role of Core Markets (Journal of Real Estate Finance & Economics), 54, 297-337.

- The projected changes in the national index apply universally across all locations. Geographic variation is maintained only through observed differences at the starting point. This assumption is consistent with the Board's stress testing principles of simplicity, consistency, and comparability.

(5) Questions

Question B13: The Board seeks comment on the alternative of using a vector autoregressive model to model CRE vacancy rate, rent index, and price index, as compared to the Board's current approach of individual autoregressive models?

Question B14: The Board seeks comment on additional factors that should be considered in modeling CRE vacancy rate, rent index, and price index, as compared to the set of factors currently included in the Board's specification.

Question B15: The Board seeks comment on the current assumption of a common, national path of changes in CRE vacancy rate, rent index, and price index in the supervisory stress test, as compared to an alternative where scenario severity differs across locations.

Question B16: The Board seeks comment on its current approach of estimating one regression per property type for the projection of CRE vacancy rate, rent index, and price index, as compared to an alternative model that is pooled at a different level of granularity.

e. Integration of Model Sub-Components and Aggregation of Results

The purpose of this section is to describe the process used to construct the loan-level dataset, generate model-projected expected loss for each loan, and aggregate loan-level expected loss projections to the firm-portfolio level. The firm-portfolio level losses are then passed on to the Provisions Model (see Section B of Aggregation).

(1) Model Specification

Model-projected $\widehat{PD}^*_{i,t}, \widehat{LGD}_{i,t}, \widehat{EAD}_{i,t}$ are assigned for each loan and each quarter in the projection horizon by applying the model specifications, estimated coefficients (PD, LGD), and/or assumptions (EAD), based on Schedule H.2 reported data, which is described further in section B.ii.e.(3).

The product of the output from each of the three main model sub-components is calculated; this product represents expected loss ($\widehat{EL}_{i,t}$) for each loan i and projection quarter t:

Equation B17 – Loan-Level Expected Loss Projection

$$\widehat{EL}_{i,t} = \widehat{PD}^*_{i,t} * \widehat{LGD}_{i,t} * \widehat{EAD}_{i,t}$$

Next, the Board aggregates the loan-level expected loss projections at the firm-portfolio level. There are two main components of this calculation: (1) expected losses from loans that are not observed to be in default as of the exercise date (non-default), and (2) expected losses from loans that are observed to be in default as of the exercise date:[110]

Equation B18 – Firm-Portfolio-Level Expected Loss Projection

$$loss_{f,y,t} = loss\_nondefault_{f,y,t} + \sum_{p \in P} loss\_default_{f,y,p,t}$$

The first component, firm-portfolio-level losses from non-default loans, is computed as the sum of expected losses from all non-default loans i within firm f and portfolio y:

Equation B19 – Firm-Portfolio-Level Losses from Non-Default Loans

$$loss\_nondefault_{f,y,t} = \sum_{i \in f,y} \widehat{EL}_{i,t}$$

[110] As described in section B.ii.a, loans that are reported at least 90 days past due, placed on non-accrual status, or extended with a below investment grade rating are assumed to be in default as of the exercise date.

The second component, firm-portfolio-level losses from default loans, is computed based on several additional assumptions. The main assumption is that the default event occurs immediately, but that losses from such loans are not incurred instantaneously (i.e., in a single period), rather the losses amortize over the projection horizon. Additionally, the Board assumes that the loss severity for such loans depends on the scenario severity over the entire projection horizon (rather than in a single period). To implement these assumptions, LGD scaling factors are first computed separately for each property type, based on the weighted average of modeled LGD for non-default loans:

Equation B20 – LGD Scaling Factor

$$lgd\_scale_{p,t} = \frac{\sum_{i \in \mathrm{p}} outstanding\_balance_i \ * \ (\widehat{LGD}_{i,t}/\widehat{LGD}_{i,t=0})}{\sum_{i \in \mathrm{p}} outstanding\_balance_i}$$

where $outstanding\_balance_i$ is the outstanding balance at the starting point ($t = 0$) for all non-default loans i within property type p, and ($\widehat{LGD}_{i,t}/\widehat{LGD}_{i,t=0}$) is the cumulative growth rate of modeled LGD from the starting point to quarter t for loan i.

Firm-portfolio-level losses from default loans are computed as:

Equation B21 – Firm-Portfolio-Level Losses from Default Loans

$$loss\_default_{f,y,p,t} = \frac{\sum_{i \in f,y,p} \widehat{EL}_{i,t=0} * lgd\_scale_{p,t}}{9}$$

where $\sum_{i \in f,y,p} \widehat{EL}_{i,t=0}$ is the sum of model-projected expected loss for all loans i within firm f, portfolio y, and property type p as of the starting point, and $lgd\_scale_{p,t}$ is the property-type-specific scaling factor defined in Equation B20.

Final, quarterly firm-portfolio-level loss rates are expressed as:

Equation B22 – Quarterly Firm-Portfolio-Level Loss Rates

$$loss\_rate_{f,y,t} = \frac{loss_{f,y,t}}{bal_{f,y,t}}$$

where $loss_{f,y,t}$ are the projected loss dollars for firm f, portfolio y, and quarter t (as defined in Equation B18), and $bal_{f,y,t}$ are the exogenously provided balances for firm f, portfolio y, and quarter t.

There are several types of firm portfolios for which the above logic for projection of losses cannot be implemented. First, loans within immaterial portfolios are not required to be reported on Schedule H.2. Therefore, losses on balances within these portfolios cannot be projected using the loan-level CRE model. For these portfolios, the 50th percentile of estimated loss rates across all firms that report a material balance within the same Schedule HC-C category is applied to the firm's immaterial portfolio balances. Second, loans from other, material firm portfolios are reported on Schedule H.2 without enough valid data to be assigned model projected expected loss.[111] For these portfolios, the Board assigns losses based on the 90th percentile of all firm-portfolio loss rates within the same Schedule HC-C category.[112]

(2) Rationale

As described above, the Board assumes that losses for loans that are considered in default as of the starting point are amortized, or spread out, over the entire projection horizon. This assumption is made so that losses from such loans are not realized by the firms immediately, in the first projection quarter. Because the default model for these loans is deterministic, an assumption of exact timing of loss (that is, in a single, specific projection quarter) would ignore

[111] Portfolios without enough valid data to be assigned a model projected expected loss are defined as having more than 50 percent of exposure not reported with sufficient information to assign modeled PD or modeled LGD.
[112] This treatment is consistent with the supervisory stress test model policy around "treatment of missing or erroneous data" described in the Stress Testing Policy Statement.

the inherent uncertainty in the loan resolution process. This assumption also avoids a large spike in projected loss that could have unintended effects on the Provisions Model (see Section B of the Aggregation Models Description). The assumption that losses from such loans evolve according to the averaged modeled LGD for non-default loans of the same property type is made so that the evolution of losses for such loans is sensitive to the macroeconomic scenario.

(3) Data and Data Adjustments

Loans reported on Schedule H.2 as of the exercise date comprise the sample of loans which are assigned modeled PD, LGD, and EAD. Based on the information that is required by the PD, LGD, and EAD model specifications, the Board implements several data treatment steps to prepare the loan-level data for forecasting. These steps are undertaken to ensure that projections can be generated for each reported loan and that the variable transformations in the forecast dataset are consistent with those implemented in the estimation dataset(s).

- Loans are assigned to one of the two main loan categories—income-producing and construction—based on the 'Line Reported on FR Y-9C' field on Schedule H.2. Loans reported under options 1, 2, 7, or missing this information on Schedule H.2, and reported without NOI information, are assigned to construction. All other loans are assigned as Income Producing.
- The loan origination balance, used to determine LTV ratio at origination, is defined as the sum of the committed balance plus cumulative charge-offs as of the earliest reported origination date for each loan.
- The average loan length, or tenor, for each firm and loan type (income-producing or construction) is computed and assigned to loans that replace previously matured loans in the projection horizon (see Section B.ii.c for more information).
- Loans are evaluated to determine whether reported information is sufficient to assign a modeled PD or modeled LGD. If not, they are flagged for the assignment of a synthetic PD or LGD (described in Sections B.ii.a and B.ii.b).
- CRE market conditions provided by the third-party data vendor (price index, rent index, and vacancy rate) are seasonally adjusted using the X11 procedure.
- Loans are assigned macroeconomic (house price index, unemployment rate) and CRE market characteristics (price index, rent index, vacancy rate) based on their reported location and property type.
- U.S. loans that cannot be mapped to a valid county as provided in the macroeconomic scenario data are assigned a state-level series. If the loan cannot be mapped to a state, it will receive the national series.

- U.S. loans that cannot be mapped to a market (as defined by the third-party data vendor) are assigned a weighted average of CRE market characteristics at the Census district, region, or national level, at the most granular mapping level available.
- International (non-U.S.) loans are assigned a simple average of model variables across six large gateway markets (New York, Boston, Washington D.C., Chicago, San Francisco, Los Angeles).[113] This adjustment assumes that CRE conditions in international markets are more likely to be correlated with the largest U.S. markets than the average U.S. market. These markets tend to be the most liquid, transparent, and least susceptible to idiosyncrasies that are not representative of the international market.
- Loans reported under property type option 8 (Mixed), 9 (Land and Lot Development), 10 (Other), or 11 (Healthcare), are assigned the market-level average of CRE market characteristics across the five property types provided by the third-party CRE market data vendor (Retail, Industrial, Hotel, Multi-family, Office). This adjustment assumes that market conditions in these property types, for which data is unavailable, are best represented by the entirety of the CRE market rather than a specific sector.
- Loans reported under property type option 5 (Homebuilders except condo) or 6 (Condo/Co-op) are assigned the CRE market characteristics for Multi-family provided by the third-party data vendor. This adjustment assumes that market conditions in these property types, for which data is unavailable, are best represented by conditions in the multi-family market.
- Origination values of price and rent indices are determined as of the loan's origination date, or as of the earliest available value in the case that the time series starts after the loan's origination date.
- For all additional model purposes, loans reported under property type option 11 (Healthcare) are treated as Other loans and loans reported under property type option 12 (Warehouse/Distribution) are treated as industrial loans.
- Loan age is calculated as the number of quarters from loan origination to the current projection quarter. Loans that replace previously matured loans have their loan age reset to zero.
- Time to maturity is computed based on the difference between the loan's reported maturity date and the current projection quarter.

(4) Assumptions and Limitations

As mentioned above, the main assumptions of the aggregation component are that (1) firm-portfolio-level losses can be constructed from the sum of loan-level projected losses, (2) losses from defaulted loans do not occur instantaneously (in a single period), but rather amortize over the projection horizon, and (3) the loss severity for defaulted loans depends on the scenario

[113] Gateway markets include data from both urban and suburban locations within the market, as defined by the vendor.

severity over the entire projection horizon (rather than in a single period). Since the default model for these loans is deterministic, an assumption of exact timing of loss (that is, in a single, specific projection quarter) would ignore the inherent uncertainty in the loan resolution process. This assumption also avoids a large spike in projected loss that could have unintended effects on the Provisions Model (see Section B in the Aggregation Models Description). The assumption that losses from such loans evolve according to the averaged modeled LGD for loans of the same property type is made so that the evolution of losses for such loans is sensitive to the macroeconomic scenario.

(5) Questions

Question B17: The Board seeks comment on an alternative model framework that includes the segmentation of risk sensitivity by loan type (income-producing vs. construction) and/or property type, as compared to the Board's current approach of modeling all CRE loans jointly.

f. Ad-hoc Adjustments

The CRE model makes an adjustment for Federal Deposit Insurance Corporation (FDIC) shared-loss agreements (SLAs). The FDIC absorbs a portion of certain losses on specific assets sold as part of the resolution of a failing institution, while the purchaser or "Assuming Institution" only absorbs the remaining losses. The percentage of losses absorbed by the FDIC varies according to the terms of the SLA. Projected losses on CRE loan portfolios that have SLAs are adjusted downwards to account for the portion absorbed by the FDIC.

C. First Lien Mortgage Model

i. Statement of Purpose

The Domestic First Lien Mortgage Loss model (First Lien Model) is used to project loan losses and provisions on domestic first lien mortgages, which are first lien, closed-end[114] exposures secured by one- to four-family residential real estate located in the United States, as defined by the FR Y-9C, that are held for investment at amortized cost.

The First Lien Model is important for accurately assessing whether firms would be sufficiently capitalized in a severe stress scenario, because stress in the residential real estate sector could lead to significant losses to mortgage portfolios. Residential real estate, the majority of which consists of first lien mortgages, was exposed to significant stress during the 2008 financial crisis. During this period, delinquency rates on residential real estate peaked at over 11 percent.[115] This stress in the housing market was a primary driver of the decision of the Board in 2009 to conduct the Supervisory Capital Assessment Program, to assess the capital adequacy of the largest U.S. BHCs during a severe recession.[116] Considering the experience of the 2008 financial crisis and the stress on residential real estate exposures during this period, the Board has determined that accounting for the ability of firms to withstand severe stress in the residential real estate market is vital to the safety and soundness of the financial system.

Given the size and complexity of the mortgage market in the United States, this section first briefly describes the overall market. After defining the subset of mortgages to which the Board applies the First Lien Model, the rest of this section describes the model itself.

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[114] Loans are "closed-end" when a fixed amount is borrowed with a scheduled repayment date, as opposed to "open-ended" loans where the credit line remains open and the loan amount can increase or decrease over time.
[115] *See* Charge-Off and Delinquency Rates on Loans and Leases at Commercial Banks, Federal Reserve Board of Governors. https://www.federalreserve.gov/releases/chargeoff/.
[116] *See* The Supervisory Capital Assessment Program: Overview of Results. Board of Governors of the Federal Reserve System, May 7, 2009, https://www.federalreserve.gov/newsevents/files/bcreg20090507a1.pdf.

a. Overview of the U.S. Mortgage Market

Mortgage lenders have the option to keep originated loans on their balance sheet (known as "portfolio loans") or sell them to third parties. Many of these third parties package multiple loans into securities ("mortgage-backed securities" or "MBS") or guarantee such securities issued by third parties. These securities are then sold to investors. Some of the major third parties are described below:

- The Government National Mortgage Association (known as "Ginnie Mae") is a Congressionally chartered corporation within the U.S. Department of Housing and Urban Development. Ginnie Mae works with private parties that issue mortgage-backed securities consisting of loans originated under government programs (such as Federal Housing Administration (FHA) or Veterans Affairs (VA) mortgages) and guarantees the servicing performance of the mortgage-backed securities issuer. The underlying loans are partially or fully insured by the relevant government agencies (most commonly FHA or VA).
- The Federal National Mortgage Association (known as "Fannie Mae") and the Federal Home Loan Mortgage Corporation (known as "Freddie Mac") are companies chartered by Congress to provide liquidity, stability, and affordability to the mortgage market. Fannie Mae was chartered in 1938, while Freddie Mac was chartered in 1970. Together, Fannie Mae and Freddie Mac are known as "government-sponsored enterprises" (GSEs); since 2008, these corporations have been under the conservatorship of the Federal Housing Finance Agency. Fannie Mae and Freddie Mac buy eligible mortgage loans from lenders and issue mortgage-backed securities, guaranteeing the securities against credit losses. Loans are eligible for inclusion in GSE mortgage-backed securities if they meet certain criteria, including a maximum loan amount (varying by year and by geography), minimum credit quality standards (such as borrower credit scores), and loan features (loans generally must have fixed, rather than adjustable, interest rates), among other features. Mortgage-backed securities guaranteed by Fannie Mae, Freddie Mac, or Ginnie Mae are known as "agency MBS."
- Private parties can also purchase loans and package them into mortgage-backed securities. These securities are known as private label mortgage-backed securities, or "PLS." In the years leading up to the 2008 financial crisis, private label mortgage-backed securities became popular for securitizing certain mortgages, such as subprime mortgages, that did not meet the criteria for inclusion in a GSE mortgage-backed security. The First Lien Model accounts only for loan losses on portfolio loans.

Firms may continue servicing loans after they are sold to third parties; however, these loans are no longer on the firm's balance sheet, and the firm is no longer responsible for the credit losses on loans after they are sold. Firms may also purchase mortgage-backed securities from the parties listed above or other third parties; the Board accounts for changes to the fair value of mortgage-backed securities owned by firms via the Securities Model.[117] Additionally, as described throughout this section, the Board assumes that firms will not incur losses on loans originated under government programs (such as FHA or VA loans), even if these loans are portfolio loans, as these loans are partially or fully insured by the U.S. government. Finally, when underwriting defects in a loan are discovered after it is sold to Fannie Mae and Freddie Mac, the GSE can require that the lender repurchase the loan for its face value; these repurchased loans are accounted for in the First Lien Model. As detailed later in this section, loans repurchased from GSEs are more likely to become delinquent, due to their underwriting defects.

b. *Summary of the First Lien Model*

The Board estimates the First Lien Model using historical data on first lien payment status and loan losses, loan characteristics, and economic conditions. The model projects losses at the loan level with an expected-loss framework, as described in Section III.A in the Enhanced Transparency and Public Accountability Proposed Rule, using data on firm-reported loan characteristics from the FR Y-14M report and economic conditions defined in the Board's supervisory stress test scenarios. All firms with material portfolios are required to report data on FR Y-14M, Schedule A (First Lien).[118] Firms with portfolio balances that are below the materiality threshold have the option of submitting or not submitting the schedule.

[117] *See* Section A in the Market Risk Models Documentation (Securities Model).

[118] FR Y-14M Instructions, at 4. For firms subject to category IV standards, material portfolios are defined as those with asset balances greater than $5 billion or with asset balances greater than ten percent of Tier 1 capital on average for the four quarters preceding the reporting period. For firms subject to category I, II, or III standards, material portfolios are defined as those with asset balances greater than $5 billion or asset balances greater than five percent of Tier 1 capital on average for the four quarters preceding the reporting period.

The expected-loss framework consists of a PD component, an LGD component, and an EAD component. Each of these components is projected using models detailed throughout this model description. The model projects PD, LGD, and EAD by applying the model parameters, along with some adjustments described in this model description, to specific loans from the FR Y-14M regulatory report. The model outputs projected losses under the hypothetical scenario.

ii. Model Description

The First Lien Model projects loan losses and provisions on first lien mortgages secured by one- to four-family residential real estate located in the United States, as defined in the FR Y-9C, using an expected loss framework. As described in more detail in Section C.ii.a, the PD model projects the probability that a loan transitions to a different payment status (i.e., current, delinquent, default, and paid off) based on the prior status of the loan as well as characteristics of the loan and the macroeconomic environment. For modeling purposes of the supervisory stress tests, the Board defines first lien mortgages as in default when they are 180 days or more past due, or if the loan status is marked as "real estate owned" (REO)[119] or "involuntary liquidation."[120] The Board defines first lien mortgages as delinquent when they are 90 days past due or in foreclosure proceedings, unless they meet the definition of default. Current and delinquent loans may also transition to a paid-off status if they are paid in full.

Due to the fundamental difference in contractual terms between adjustable-rate mortgages (ARMs) and fixed-rate mortgages (FRMs)—namely, the fact that ARM interest rates vary over the course of the loan, while FRM interest rates generally do not—the Board estimates

[119] A loan status of "REO" indicates that the lender has taken possession of the collateral.
[120] A loan status of "involuntary liquidation" indicates that that the loan has been liquidated either through foreclosure proceedings or another settlement option resulting in incomplete repayment of principal.

separate PD models for the two product types. In each period, each model uses a regression framework to estimate the probability that a loan transitions from one payment status to another status (e.g., from current to delinquent or from delinquent to default) over a single quarter.

The model generates a probability of default and payoff during a quarter, conditional on the loan's payment status at the end of the prior quarter. The model assumes default and paid-off to be terminal payment statuses and that loans in the model cannot transition out of those payment statuses. Support for treating these statuses as terminal is available in Section C.2.a.(2). Mathematically, the model is specified in Equation C1:

Equation C1 – First Lien PD Model Specification

$$PR\left(S_{i,t+1} \middle| S_{i,t}\right) = f\left(X_{i,t}, Z_t\right)$$

where:

- *i* represents the loan;
- *t* represents time;
- $S_{i,t}$ represents the status of loan *i* in time *t;*
- $PR\left(S_{i,t+1} \middle| S_{i,t}\right)$ represents the probability (PR) that the loan is in a given payment status *S* in period *t+1* given the payment status *S* in period *t*;
- $X_{i,t}$ represents loan and borrower characteristics; and
- Z_t represents one or more of the macroeconomic variables included in the supervisory scenarios.

Collectively, these models project a probability of default, conditional on product type, initial payment status, loan and borrower characteristics, and economic conditions over the projection horizon. Section C.ii.a contains a detailed description of the exact variables and assumptions used to fit the PD model equations, as well as alternatives to the model used in the supervisory stress test.

The LGD model is described in detail in Section C.ii.b. The LGD model estimates the share of the balance expected to be lost at liquidation based on loan and borrower characteristics in addition to the macroeconomic environment. The LGD model is run in two stages. In the first stage, the length of time projected to elapse between default and liquidation is assigned. This length of time is calibrated for all loans as 22 months (as discussed in Section C.ii.b.(2)). In the second stage, this timeline is used as an input to a regression model used to calculate the loss severity (the "loss severity" model). The loss severity model is made up of three equations, corresponding to "Prime," "Alt-A," and "Subprime" loans, where the categorizations are determined based on characteristics of the loan, such as credit score and loan-to-value (LTV) at origination.[121] Each equation is specified as in Equation C2:

Equation C2 – First Lien LGD Model Specification

$$LGD_{i,t} = f\left(X_{i,t}, T_i, Z_{T_i}\right)$$

where:

- i represents the loan;
- t represents the time of default;
- $LGD_{i,t}$ represents the loss severity rate of loan i that enters default at time t;
- $X_{i,t}$ represents a set of loan and borrower characteristics;
- T_i represents the liquidation timeline for loan i; and
- Z_{T_i} represents one or more of the macroeconomic variables included in the supervisory scenarios at the time of liquidation.

The Board assumes that eight months of the liquidation timeline is allocated to the period during which the property becomes REO. The calibration of this period is discussed in Section C.ii.b. Net losses on loans in REO status are treated as other real estate owned (OREO) expenses, which are a component of pre-provision net revenue. The LGD, for purposes of determining credit losses on first lien mortgages, is calculated as the total losses, minus the

[121] A full description of how loans are categorized into "Prime," "Alt-A," and "Subprime" is available in Section C.ii.b.(1).

portion designated as OREO expenses, as a share of the EAD. The pre-provision net revenue projections capture the effect of OREO expenses.

The Board assumes EAD for first lien mortgages to be the unpaid principal balance of the loan at the start of the projection horizon. Additional details on the EAD model are available in Section C.ii.c.

The model projects PD, LGD, and EAD by applying the model parameters to specific loans from the FR Y-14M regulatory report to produce loss rates; the PD model also produces payoff rates (see Section C.ii.d for more details). These loss rates and payoff rates are then applied in the Retail Loss Aggregation process, detailed in Section C.ii.e, to project loss dollars using balances produced by the balance sheet line-item projections calculator based on data reported in FR Y-14Q, Schedule M.1 (Balances).[122] Total loss dollars are projected as the sum of projected losses on the existing portfolio plus the projected losses on projected new origination balances during the projection period. Additional adjustments to losses are made at this stage to account for certain portfolio-level factors reported on the FR Y-14 reports.

A detailed description of each of the model components is below. First, the structure, input data, and variables used to define the model are described. Next, support for the modeling decisions—including the model structure and the individual variables included in the model—is provided. Then, the data cleaning process and any adjustments applied to the input data are detailed. Finally, alternatives to the chosen modeling approaches are discussed, along with questions to solicit feedback from the public.

[122] *See* Section A in the Aggregation Models Documentation (Balances Model).

a. Probability of Default Model

(1) Description

As described above, in the introduction to Section C.ii, the PD model projects the probability that a loan transitions to a different payment status (i.e., current, delinquent, default, and paid off), based on the prior status of the loan as well as characteristics of the loan and the macroeconomic environment (see Equation C2).

To estimate the PD model, the Board uses historical, monthly loan-level data provided by a third-party vendor from many servicers of first-lien mortgages (the “First Lien PD Data”). The First Lien PD Data covered more than half of the overall mortgage market as of the start of the 2008 financial crisis, the largest housing market stress event for which data are available. The dataset includes many of the same variables as the FR Y-14M report, a key advantage for its use in estimating the PD model. The PD model is estimated using a 10 percent sample[123] of this dataset, tracking loan performance between January 2002 and September 2022 for loans originated between 2002 and 2021.[124]

Using the variables in the First Lien PD Data described below, the model defines the status of each loan in each quarter, as follows:

- **Default**, if the next payment due date associated with the loan is 180 or more days prior to the reporting date (in other words, the loan is 180 or more days past due), or if the payment status of the loan is marked as “REO” or “involuntary liquidation,” indicating that a lender has taken possession of the property or the loan has been liquidated with incomplete repayment of principal.
- **Delinquent**, if a loan is not in default, but the loan is reported to be 90 or more days past due or is in foreclosure proceedings.
- **Paid-off**, if the loan is marked in the First Lien PD Data as having been paid-off.
- **Current**, if a loan is not more than 90 days past due and none of the above criteria are triggered.

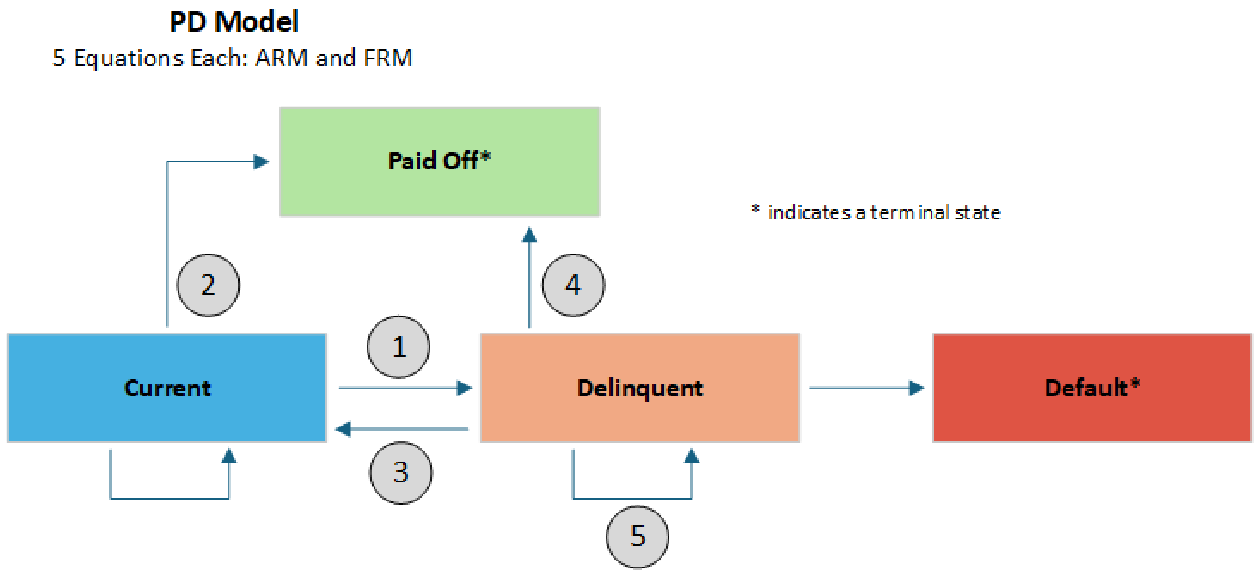
[123] *See* Section C.ii.a.(3) for discussion of sampling.
[124] *See* Section C.ii.a.(3) for discussion of the period of data used to estimate the PD model coefficients.

While loans can have other terminal states, such as loan sales or the transfer of loan servicing rights, the Board does not forecast these outcomes in the PD model because the vendor dataset does not allow us to distinguish between a sale of the loan, which would remove its credit risk from the firm's balance sheet, and that of the servicing rights alone, which would not.

With these statuses defined, the model projects the probability of a loan moving from one status to another status. Current loans can remain current, or transition to “delinquent” or “paid-off”; delinquent loans can remain delinquent, or transition to “current”, “default”, or “paid-off”. A series of five equations, marked in the figure below, produce these probabilities. These five equations are estimated separately for ARMs and FRMs, for a total of ten transition equations. As discussed in more detail in Section C.ii.a.(2), “default” and “paid-off” are considered to be terminal statuses in that loans are not able to transition from these statuses back to other statuses; treating default as a terminal status is consistent with the stress testing principle of conservatism. A visual depiction of these statuses and the transitions among them is available in Figure C1.[125]

[125] The probability of a loan remaining current in a given period is determined based on the probability of it not transitioning to paid-off or delinquent in that period. The probability of a loan defaulting from delinquent in a given period is based on the probability of it not being paid-off, returning current, or transitioning to default.

Figure C1 - First Lien PD Model Equations



Each of the ten equations incorporates loan, borrower, and macroeconomic characteristics associated with the transition it predicts. These characteristics are chosen to account for the most important factors in determining the likelihood of the transition. Mathematically, each equation is estimated as the probability of a loan is in a given status in the next quarter, given that the loan either is in that status or is in the "base" status (current for loans that begin as current, or default for loans that begin as delinquent) in the next quarter.[126] For instance, as shown mathematically in Equation C3, the current-to-delinquent ("C" to "L", where "L" is short for "late") expression is the probability that a loan (i) that is current (C) in a given quarter t transitions to delinquent (L) in the next quarter (t+1), given that it is either current or delinquent in the next quarter: [127]

Equation C3 – First Lien PD Structure

$$\Pr\left(L_{i,t+1} \mid C_{i,t} \text{ } and \text{ } [C_{i,t+1} \text{ } or \text{ } L_{i,t+1}]\right)$$

[126] Base statuses are denoted in Figure C1 based on the arrows for which there is no equation number attached. See the review of literature in Section C.ii.a.(2) for more information and support for the statistical approach.
[127] In particular, in this example, loans that payoff in the next quarter are not included in the data when estimating this equation. Meanwhile, in the current-to-payoff equation, loans are included if they remain current or payoff in the following quarter, but loans that become delinquent are not included in the data used to estimate the current-to-payoff equation. The implementation of this approach is described in more detail in Section C.ii.a.(2).

The full specification and coefficients of all 10 equations are available in Tables C1-C4. Each transition is shown separately and denoted using "C" = "Current"; "L" = "Delinquent" (or "Late"); "P" = "Paid-off"; and "D" = "Default". Support for the model structure and the inclusion of the particular variables in these equations is available in Section C.ii.a.(2); detailed explanations of the variables are included in this section as well. As described in that sub-section, variables are chosen for inclusion in each equation separately; in many cases, variables that are important to explain certain transitions are not relevant for explaining other transitions. Finally, a discussion of alternative modeling approaches and other variables considered but not included in the model is available in Section C.ii.a.(4).

Note that the variable descriptions in the table below often refer to "knots." Knots are the specific values that separate a variable into segments that are used in a model. These knots are points where the incremental impact of the variable on the output can change. This accounts for non-linear effects across the range of a variable, as its impact might not be consistent across all values. For example, in the current-to-delinquent transition model, an origination credit score knot at 660, which accounts for credit score values above 660, considers the increased relative sensitivity of delinquency risk to changes in credit score at values above 660 compared to values less than 660.[128] More information about knot selection when using "splines" is available in Section C.ii.a.(2).

More information about the definition of each of these variables is available in Section C.ii.a.(2).

[128] Knot coefficients are interpreted as additive. Following this example, the effect of credit scores above 660 would be based on the sum of the coefficient on the credit score and the coefficient of the credit score knot at 660.

Table C1 - FRM, Transitions from Current

FRM, Transitions from Current		**Current-to-Delinquent**		**Current-to-Payoff**	
Parameter	**Variable Description**	**Estimate**	**Std.Err.**	**Estimate**	**Std.Err.**
Intercept	-	-0.0114	0.1034	-3.4819	0.1944
Origination credit score	Credit score at origination	-	-	-	-
	Origination credit score	-0.0062	0.0001	-	-
	Knot at 660	-	-	0.0022	0.0001
	Knot at 700	-0.0075	0.0004	-	-
	Knot at 780	-0.0109	0.0018	-	-
	Indicator for missing origination credit score	-4.3985	0.0966	0.6918	0.0123
Industry COVID-19 forbearance rate	For periods during the COVID-19 pandemic, the share of portfolio loans at large banks in forbearance in a given period	13.8188	0.5349	-	-
GSE repurchase flag	Indicator variable for repurchased from GSE	0.9424	0.0891	1.9478	0.0309
Change in unemployment rate over previous year	Percentage point change in the unemployment rate compared to one year prior	0.1171	0.0038	-	-
Change in house price index (HPI) over previous year	Percentage change in HPI compared to one year prior	-2.1231	0.0893	1.7611	0.0338
Interest only indicator	Indicator for interest only loan	0.7418	0.0352	-	-

FRM, Transitions from Current		**Current-to-Delinquent**		**Current-to-Payoff**	
Origination year[129]	Origination year	-	-	-	-
	Originated in 2006	0.2880	0.0218	-	-
	Originated in 2007	0.3688	0.0200	-	-
	Originated in 2008	-0.0662	0.0295	-	-
	Originated in 2009	-0.6128	0.0459	-	-
	Originated in 2010	-0.5953	0.0563	-	-
	Originated in 2011	-0.6488	0.0561	-	-
	Originated in 2012+	-0.6376	0.0283	-	-
Jumbo loan interaction with origination year	Product of jumbo loan indicator and origination year indicator	-	-	-	-
	Jumbo; 2007 origination	0.2238	0.0348	-	-
	Jumbo; 2008 origination	0.5473	0.0657	-	-
	Jumbo; 2010 origination130	-0.5106	0.2251	-	-
	Jumbo; 2011 origination	-0.5418	0.1934	-	-
	Jumbo; 2012+ origination	0.0070	0.0289	-	-
Loan age	Loan age in months	-	-	-	-
	Loan age	0.0480	0.0033	0.1091	0.0011

[129] The "Originated in 2009", "Originated in 2010", "Originated in 2011", and "Originated in 2012+" terms are used to estimate the model coefficients; however, as described later in this section, these terms are not applied when projecting PD. See the below discussion for more information.

[130] The "Jumbo; 2010 origination", "Jumbo; 2011 origination", "Jumbo; 2012+ origination" terms are used to estimate the model coefficients; however, to ensure model outputs are sufficiently conservative, these terms are not applied when projecting PD. The treatment of 2009 and later originations is described later in this section. Based on the Board's experience and expertise, using analysis of the historical First Lien Data, the Board determined that there is limited value in accounting for whether a loan originated prior to 2007 is a jumbo loan; therefore, jumbo loans are only treated differently from other loans if they are originated in or after 2007.

FRM, Transitions from Current		Current-to-Delinquent		Current-to-Payoff	
	Knot at 12 months	-0.0158	0.0046	-0.1085	0.0011
	Knot at 24 months	-0.0343	0.0019	-	-
Retail indicator	Indicator for whether loan originated through retail channel	-0.1899	0.0135	-	-
Origination spread	Difference between origination interest rate and 10-year Treasury rate in month of origination	-	-	-	-
	Origination spread	0.0368	0.0380		-
	Knot at 1%	0.3456	0.0431	-	-
	Knot at 3%	-0.2351	0.0148	-	-
Loan term	Indicator for term less than 30 years	-0.3772	0.0174	0.0581	0.0057
Updated LTV	Original LTV scaled by the change in house price index since origination[131]	-	-	-	-
	Less than 50% flag	-1.6834	0.0301	2.6661	0.1262
	50%-60% flag	-1.7847	0.0343	2.6809	0.1262
	60%-70% flag	-1.6194	0.0305	2.6867	0.1262
	70%-80% flag	-1.4917	0.0283	2.6208	0.1262
	80%-90% flag	-1.2320	0.0262	2.4261	0.1263
	90%-100% flag	-0.9783	0.0255	2.0391	0.1267
	100%-110% flag	-0.7902	0.0257	1.7820	0.1275
	110%-130% flag	-0.4879	0.0249	1.4036	0.1289
	130%-150% flag	-	-	0.8403	0.1415

[131] Throughout the PD model, the calculation of updated LTV does not account for any change in loan balance from origination. This may lead to understating of the risk of loans that have balances similar to the origination amounts, while overstating the risk of loans that have balances that have declined significantly from their origination amounts. The Board tested accounting for changes in loan balance and determined that adjusting this assumption would lead to changes in losses, as a share of risk-weighted assets, by no more than 0.02 percent for any firm.

FRM, Transitions from Current		**Current-to-Delinquent**		**Current-to-Payoff**	
Burnout	Proxy for borrower propensity to prepay that is otherwise unobserved[132]	-	-	-0.0168	0.0005
Seasonality indicator	Indicator for calendar quarter	-	-	-	-
	Q1	-	-	0.1442	0.0056
	Q2	-	-	0.1031	0.0055
Loan size (Log)	Natural log of loan size at origination	-	-	-	-
	Loan size	-	-	-0.4068	0.0134
	Knot at $60,000	-	-	0.6922	0.0144
Investment indicator	Indicator for whether occupancy type is investment property	-	-	-0.0688	0.0102
Secondary residence indicator	Indicator for whether occupancy type is secondary residence	-	-	-0.2095	0.0113
Pre-2003 origination indicator	Flag whether loan originated before 2003	-	-	1.1741	0.0410
Pre-2003 origination after 2003 indicator	Flag whether loan originated before 2003 and observation after 2003	-	-	-0.8776	0.0545
Refinance incentive	Difference between Primary Mortgage Market Survey (PMMS) 30-year fixed-	-	-	-	-

[132] Formally, this is calculated as the cumulative sum of the log of the ratio of the average mortgage rate at origination to the contemporaneous average mortgage rate for all periods through the current period. A larger “burnout” is indicative of the borrower having turned down previous chances to prepay even when refinance appears rational, suggesting the borrower has an otherwise unobservable lower propensity to prepay.

FRM, Transitions from Current		Current-to-Delinquent		Current-to-Payoff	
	rate mortgage rate at origination compared to current level				
	Difference	-	-	0.9265	0.0045
	Knot at 1%	-	-	-0.7694	0.0105
Yield curve spread	Difference between 10-year and 3-month Treasury rates	-	-	-0.1145	0.0027

Table C2 - FRM, Transitions from Delinquent

FRM, Transitions from Delinquent		Delinquent-to-Current		Delinquent-to-Delinquent		Delinquent-to-Prepay	
Parameter	**Variable Description**	**Estimate**	**Std.Err.**	**Estimate**	**Std.Err.**	**Estimate**	**Std.Err.**
Intercept	-	2.6093	0.2176	4.3650	0.2039	-1.1044	0.4620
Judicial foreclosure state[133] indicator	Flag whether state uses a judicial foreclosure regime	-	-	-0.0904	0.0235	-	-
Industry COVID-19 forbearance rate	For periods during the COVID-19 pandemic, the share of portfolio loans at large banks in forbearance in a given period	-	-	-6.9387	0.6529	-	-
Change in HPI over previous year	Percentage change in HPI compared to one year prior	-	-	-	-	-	-
	Change in HPI	4.2465	0.1615	3.8554	0.1319	6.5049	0.9235
	Knot at 0	-	-	-	-	-0.8478	1.3102
Origination credit score	Credit score at origination	-	-	-	-	-	-

[133] Judicial foreclosure refers to a process where foreclosures go through court proceedings. Many states have processes to allow lenders to foreclose on the property without going through court proceedings (non-judicial foreclosures). Historically, loss severity has been higher in states with judicial foreclosure compared to states with widely-used non-judicial foreclosure options. When projecting first lien losses, the model treats all loans identically, regardless of the foreclosure type in the state. More details are available in Section C.ii.a.(2).

FRM, Transitions from Delinquent		**Delinquent-to-Current**		**Delinquent-to-Delinquent**		**Delinquent-to-Prepay**	
	Origination credit score	-0.0039	0.0002	-0.0046	0.0002	-	-
	Indicator for missing origination credit score	-2.7094	0.1592	-3.2548	0.1395	-	-
Loan size (Log)	Natural log of loan size at origination	-0.0075	0.0169	-0.1148	0.0154	-0.0511	0.0394
Investment indicator	Indicator for whether occupancy type is investment property	-0.4098	0.0597	-0.3744	0.0502	-0.0467	0.1406
Secondary residence indicator	Indicator for whether occupancy type is secondary residence	-	-	-0.2948	0.0851	-	-
Origination spread	Difference between origination interest rate and 10-year Treasury rate in month of origination	-0.1040	0.0092	-0.0930	0.0075	-	-
Updated LTV	Original LTV scaled by the change in house price index since origination, capped at 200%	-0.0060	0.0005	-	-	-0.0208	0.0013

Table C3 - ARM, Transitions from Current

ARM, Transitions from Current		**Current-to-Delinquent**		**Current-to-Payoff**	
Parameter	**Variable Description**	**Estimate**	**Std.Err.**	**Estimate**	**Std.Err.**
Intercept	-	-1.3292	0.2662	-5.9254	0.0579
Origination credit score	Credit score at origination	-	-	-	-
	Origination credit score	-0.0051	0.0004	-	-
	Knot at 660	-0.0007	0.0008	-	-
	Knot at 720	-0.0064	0.0009	0.0038	0.0001
	Indicator for missing origination credit score	-3.7983	0.2569	0.2311	0.0213

ARM, Transitions from Current		Current-to-Delinquent		Current-to-Payoff	
Industry COVID-19 forbearance rate	For periods during the COVID-19 pandemic, the share of portfolio loans at large banks in forbearance in a given period	13.3786	1.0514	-	-
GSE repurchase flag	Indicator variable for repurchased from GSE	1.0177	0.2738	1.1476	0.1703
Change in unemployment rate over previous year	Percentage point change in the unemployment rate compared to one year prior	0.1330	0.0058	-	-
Change in HPI over previous year	Percentage change in HPI compared to one year prior	-2.7198	0.1128	1.4462	0.0463
Interest only indicator	Indicator for interest only loan	0.2471	0.0233	-0.1818	0.0084
Loan age	Loan age in months	-	-	-	-
	Loan age	0.0371	0.0051	0.0930	0.0016
	Knot at 12 months	-0.0132	0.0070	-0.0927	0.0017
	Knot at 24 months	-0.0244	0.0029	-	-
Origination year[134]	Origination year	-	-	-	-
	Originated in 2005	0.1162	0.0299	-	-
	Originated in 2006	0.4440	0.0301	-	-
	Originated in 2007	0.4303	0.0290	-	-
	Originated in 2009[135]	-0.2972	0.1057	-	-
	Originated in 2010	-0.2191	0.1319	-	-
	Originated in 2011	-0.3228	0.1270	-	-
	Originated in 2012+	-0.5128	0.0549	-	-
Retail indicator	Indicator for whether loan originated through retail channel	-0.3681	0.0178	-	-
Origination spread	Difference between origination interest rate and 10-year Treasury rate in month of origination	-	-	-	-
	Spread at origination	0.5243	0.0129	-	-
	Knot at 3%	-0.4243	0.0210	-	-

134 The “Originated in 2009”, “Originated in 2010”, “Originated in 2011”, and “Originated in 2012+” terms are used to estimate the model coefficients; however, as described later in this section, these terms are not applied when projecting PD. See the below discussion for more information.

135 *See* footnote for Origination Year in Table C1.

ARM, Transitions from Current		Current-to-Delinquent		Current-to-Payoff	
Updated LTV	Original LTV scaled by the change in house price index since origination	-	-	-	-
	Less than 50% flag	-1.9643	0.0655	1.5903	0.0547
	50%-60% flag	-1.8495	0.0648	1.6794	0.0548
	60%-70% flag	-1.6812	0.0561	1.6822	0.0545
	70%-80% flag	-1.3944	0.0502	1.5756	0.0543
	80%-90% flag	-1.0469	0.0467	1.3131	0.0546
	90%-100% flag	-0.8208	0.0461	0.9810	0.0559
	100%-110% flag	-0.6444	0.0465	0.6783	0.0590
	110%-130% flag	-0.4610	0.0452	0.3271	0.0617
	130%-150% flag	-0.3386	0.0509	-	-
Burnout	Proxy for borrower propensity to prepay that is otherwise unobserved[136]	-	-	-0.0024	0.0007
Seasonality indicator	Indicator for calendar quarter	-	-	-	-
	Q1	-	-	0.1517	0.0091
	Q2	-	-	0.1193	0.0093
Loan size (log)	Natural log of loan size at origination	-	-	-	-
	Knot at $60,000	-	-	0.1966	0.0052
Secondary residence indicator	Indicator for whether occupancy type is secondary residence	-	-	-0.2443	0.0151
Investment indicator	Indicator for whether occupancy type is investment property	-	-	-0.3546	0.0148
Fixed rate period	Length of time after origination prior to initial rate reset	-	-	-	-
	0-6 months	-	-	0.4600	0.0355
	1 year	-	-	0.0653	0.0253
	2 or 3 years	0.1951	0.0247	0.2684	0.0146
After fixed rate period indicator	Indicator whether loan after fixed rate period	0.2538	0.0476	-0.2594	0.0213

[136] *See* footnote for Burnout in Table C1.

ARM, Transitions from Current		Current-to-Delinquent		Current-to-Payoff	
Interest only after fixed rate period indicator	Interaction between interest only and after fixed rate period indicators	0.2026	0.0410	-	-
Time to initial rate reset (end of fixed rate period)	Proximity to initial rate reset	-	-	-	-
	Less than 6 months after fixed rate period	-	-	0.2740	0.0454
	Within 6 months of end of fixed rate period	-	-	0.3445	0.0256
	Less than 12 months after fixed rate period	-	-	0.2338	0.0402
	Within 12 months of end of fixed rate period	-	-	0.2884	0.0209
Rate change and initial rate reset interactions	Product of change in 3-month Treasury bill from origination to the current period and proximity to initial rate reset (referred to as “Rate Change” below)	-	-	-	-
	Rate Change for loans within 6 months after end of fixed rate period	-	-	0.0579	0.0185
	Rate Change for loans in the 6 months prior to the end of fixed rate period	-	-	0.1376	0.0102
	Rate Change for loans within 12 months after end of fixed rate period	-	-	0.0998	0.0149
	Rate Change for loans in the 12 months prior to the end of fixed rate period	-	-	0.1069	0.0080
	Rate Change for loans with fixed rate window loans between 0-6 months	-	-	0.1963	0.0160
	Rate Change for loans that are after the fixed rate window	0.1889	0.0109	-	-
Teaser after fixed rate period indicator	Indicator for teaser rate loans that are outside the initial (teaser rate) fixed rate period	0.8176	0.0774	0.2406	0.0314
Teaser after 2010 indicator	Indicator for teaser rate loans reported after 2010	0.0909	0.2133	-	-

ARM, Transitions from Current		Current-to-Delinquent		Current-to-Payoff	
Origination spread of teaser	Interaction of spread at origination and teaser indicator	-0.4718	0.1382	-	-
Origination spread over FRM rate	Difference of origination interest rate and average 30-year fixed-rate mortgage rate as of the origination date	-	-	-	-
	Spline at 1%	-	-	-0.3051	0.0183
Current spread over FRM rate	Difference of current interest rate over average 30-year fixed-rate mortgage rate in current month	-	-	-	-
	Actual level	-	-	0.3909	0.0042
	Spline at 2.5%	-	-	-0.4846	0.0250

Table C4 - ARM, Transitions from Delinquent

ARM, Transitions from Delinquent		Delinquent-to-Current		Delinquent -to-Delinquent		Delinquent -to-Payoff	
Parameter	**Variable Description**	**Estimate**	**Std.Err.**	**Estimate**	**Std.Err.**	**Estimate**	**Std.Err.**
Intercept		3.3367	0.3043	3.1178	0.2055	-2.5309	0.1050
Judicial foreclosure state[137] indicator	Flag whether state uses a judicial foreclosure regime	-0.0930	0.0492	-0.1694	0.0418	-	-
Industry COVID-19 forbearance rate	For periods during the COVID-19 pandemic, the share of portfolio loans at large banks in forbearance in a given period	-	-	-6.3727	1.4607	-	-
Change in HPI over previous year	Percentage change in house price index (HPI) compared to one year prior	4.9176	0.2389	4.4572	0.1874	6.0176	0.5498
Origination credit score	Credit score at origination	-	-	-	-	-	-
	Origination credit score	-0.0054	0.0004	-0.0055	0.0003	-	-

[137] *See* footnote for Judicial Foreclosure State Indicator in Table C2.

ARM, Transitions from Delinquent		Delinquent-to-Current		Delinquent -to-Delinquent		Delinquent -to-Payoff	
	Indicator for missing value	-3.2224	0.2927	-3.4573	0.2211	-	-
Investment indicator	Indicator for whether occupancy type is investment	-0.7622	0.0868	-0.7510	0.0699	-1.0353	0.2280
Origination spread	Difference between origination interest rate and 10-year Treasury rate in month of origination	-0.0876	0.0173	-	-	-0.1342	0.0407
Updated LTV	Original LTV scaled by the change in house price index since origination, capped at 200%	-	-	-	-	-	-
	Updated LTV	-0.0061	0.0009	-	-	-	-
	Indicator for LTV above 90%	-	-	-	-	-0.6085	0.1134

To use these models to project PD and payoff rates, the equations specified in Tables C1 – C4 are applied to each loan being projected. The probabilities of the individual transitions for a given loan's starting status (current or delinquent) are determined using these equations and then summed. The probability of a current loan remaining in the current status is equal to this sum, subtracted from one; similarly, the probability of a delinquent loan transitioning to defaulted status is equal to this sum, subtracted from one. This process is repeated throughout the 13-quarter projection period using a process known as a Markov chain. Under a Markov chain process, after each quarter the probability of a loan being in each of the four model "payment statuses" (current, delinquent, paid-off, or defaulted) is generated. These probabilities are used as the starting statuses in the next quarter, to create likelihoods that a loan is in each state in a given quarter.

Below is a discussion of other notable components of the PD model.

- *Progress of Time-Varying Factors.* The PD model makes assumptions about the progression of time-varying factors over the projection period. Generally, these factors are expected to remain constant throughout the projection period. Notably, unpaid principal balance is assumed to be constant in line with the stress testing principle of simplicity, due to potential variation in amortization schedules across loans. However, variables that predictably change over time, such as the age of the loan or the time until the interest rate on an ARM first resets,[138] are assumed to update as time elapses over the projection period.
- *Origination Year Terms.* The PD model includes terms to account for the origination year of the loan to account for unobserved differences in loan underwriting over time. The coefficients estimated on the model indicate that loans originated immediately prior to the 2008 financial crisis period (for FRMs, 2006-2008; for ARMs, 2006-2007) are substantially riskier than loans originated before or after, while loans originated in or after 2009 are substantially less risky. However, the coefficients estimated for vintages in and after 2009 may not accurately reflect the true risk of these loans, given that these loans have not been exposed to a major housing downturn. Given the uncertainty of how recent loans would behave in a housing downturn, and consistent with the stress testing principle of conservatism, the Board effectively treats loans originated in and after 2009, up to the present period, as having the same risk level as loans originated in 2002-2005 (for FRMs) or 2004 (for ARMs).[139] Additional support for the treatment of 2009 and after vintages is provided in Section C.ii.a.(2).
- *Adjustments for Option ARMs.* Due to challenges estimating a model for Option ARM loans, the PD model makes an adjustment when projecting payoff rates for these loans. An Option ARM loan is a type of adjustable-rate mortgage that allows borrowers to choose among different payment “options,” rather than requiring a fixed payment each period. Prior to the 2008 financial crisis, Option ARM loans were relatively popular, while they make up an extremely small portion (less than half of 1 percent) of loans reported across all firms on FR Y-14M, Schedule A (First Lien) in recent periods. As discussed in Section C.2.a.(3), Option ARM loans are excluded from the sample of ARMs used to fit the model, because of the unique and complex characteristics of these loans. When applying the model to project PD, Option ARMs are treated similarly to other ARMs, except that the model assumes that Option ARMs will pay off at half the rate projected by the model. This is based on lower historical prepayment rates for these loans observed in the First Lien PD Data; as evidenced by the fact that when model projections are compared to historical actual outcomes from the First Lien PD Data in a back-testing analysis, this treatment of Option ARM payoff rates improves the model fit. Given the small share of Option ARMs in the portfolio in recent years, the treatment of Option ARMs is reasonable, consistent with the Stress Testing Policy Statement principles of conservatism and simplicity, and has an immaterial impact on model results.

[138] ARMs often have a period of time after origination during which the interest rate is fixed, after which the rate floats based on market rates.
[139] Formally, because loans originated in 2008 for ARMs have the same empirical level of risk as 2004, the model treats post-2009 ARM originations as if they are the same level of risk as loans originated in 2004 or 2008.

- *Losses on Defaulted Loans.* Loans that have triggered default conditions (e.g., are 180 or more days past due at the start of the projection period) are not run through the PD model, since they have already reached terminal status; these loans are accounted for separately. As these loans have already reached default, they are assigned a PD of 100 percent. To smooth out the losses on these loans, losses on defaulted loans are assumed to be evenly spread over the first six projection quarters. More information about this treatment is available in Section C.ii.d.

(2) Support for Model Decisions

The design and specification of the first lien PD model is supported by a review of the relevant literature and industry best practices, statistical fit, and modeler expert judgment. This section describes both the support for the overall model design as well as the specific variables and transformations included in the model.

Review of Literature

Academic literature dates back to the late 1960s when von Furstenberg developed the first academic default risk model, which showed that the borrower's level of home equity at the time of origination was the most important predictor of mortgage default.[140] Since then, numerous mortgage PD models have been developed and estimated. Other examples include Demyanyk and Van Hemert, (2011); Elul, Souleles, et al. (2010); and An, Deng and Gabriel, (2021).[141]

The Board draws on the literature in developing the First Lien PD Model. One key finding for mortgage modeling, which the Board has incorporated in the First Lien PD Model is

[140] *See* von Furstenberg, G., 1969. "Default Risk on FHA-Insured Home Mortgage as a Function of the Term of Financing: A Quantitative Analysis," Journal of Finance 24(2): 459-77; von Furstenberg, G. (1970a). "Interstate Differences in Mortgage Renting Risks: An Analysis of Causes," Journal of Financial and Quantitative Analysis 5: 229-42; von Furstenberg, G. (1970b). "The Investment Quality of Home Mortgages," Journal of Risk and Insurance 37 (3): 437-45.

[141] *See* Demyanyk, Y, and Van Hemert, O. "Understanding the Subprime Mortgage Crisis." The Review of Financial Studies 24, no. 6 (2011): 1848–80.; Elul, R., N. S. Souleles, S. Chomsisengphet, D. Glennon, and R. Hunt (2010). "What 'Triggers' Mortgage Default?" American Economic Review Papers & Proceedings 100(2): 490-94; An, X., Y. Deng, S.A. Gabriel, (2021), Default Option Exercise over the Financial Crisis and beyond, Review of Finance, 25(1): 153–187.

that default and prepayment[142] are two outcome variables that must be modeled simultaneously. This feature is referred to as "competing risks". Some studies treat prepayment and default as seemingly unrelated risks,[143] that can be predicted independently of one another (in other words, an increase in prepayment probability has no impact on default probability); however, these factors are not independent in practice. The literature discussed below covers different ways for treating these competing risks.

A natural approach to modeling mortgage performance is a multinomial logit approach. A multinomial logit is a model that allows for the determination of multiple probability outcomes (such as default and payoff), where the combined probability of all the outcomes sums to one.[144] An alternative way to handle the competing risks using a logit framework, which is incorporated into the First Lien PD Model, is to estimate prepayment and default probabilities separately

[142] Prepayment occurs when borrowers pay off their loan balance in full prior to the end of the contractual term. The First Lien Model refers to the paid-off status, which more broadly encompasses prepayment as well as loans that are paid off due to reaching their contractual maturity date; however, in practice, prepayment accounts for the majority of loans that pay off.

[143] *See* Quigley, J. M. and R. Van Order (1995). "Explicit Tests of Contingent Claims Models of Mortgage Default," Journal of Real Estate Finance and Economics 1(2): 99–117; Deng, Y., J. M. Quigley and R. Van Order, 1996, Mortgage Default and Low Down-payment Loans: The Cost of Public Subsidy, Regional Science and Urban Economics 26: 263-285.

[144] *See* Zorn, P. and M. Lea, 1989. Mortgage Borrower Repayment Behavior: A Microeconomic Analysis with Canadian Adjustable Rate Mortgage Data, Journal of the American Real Estate and Urban Economics Association, 17 (1):118-36; Campbell, T.X. and K. Dietrich, 1983. The Determinant of Default on Insured Conventional Residential Mortgage Loans, Journal of Finance, 38(5): 1569-1581; Vandell, K.D. and Thibodeau, T. (1985), Estimation of Mortgage Defaults Using Disaggregate Loan History Data. Real Estate Economics, 13: 292-316; Archer, W.R., D.C. Ling and G.A. McGill, 1996, The Effect of Income and Collateral Constraints on Residential Mortgage Terminations, Regional Science and Urban Economics, 26(3-4): 235-261; Archer, W.R., D.C. Ling and G.A. McGill, 1997, Demographic Versus Option-Driven Mortgage Terminations, Journal of Housing Economics, 6(2): 137-163; Archer, W.R., P.J. Elmer, D.M. Harrison and D.C. Ling, 2002. Determinants of Multifamily Mortgage Default, Real Estate Economics, 30(3): 445-473; Ambrose, B.W. and A.B. Sanders, 2003. Commercial Mortgage-Backed Securities: Prepayment and Default, Journal of Real Estate Finance and Economics, 26(2-3): 179-196; Clapp, J.M., Y. Deng, and X. An, 2006. Unobserved Heterogeneity in Models of Competing Mortgage Termination Risks, Real Estate Economics, 34(2): 243-273; An, X., J.C. Clapp, and Y. Deng, 2010. Omitted Mobility Characteristics and Property Market Dynamics: Application to Mortgage Termination, Journal of Real Estate Finance and Economics, 41(3): 245-271; Agarwal, S., Y. Chang, and A. Yavas, 2012. Adverse Selection in Mortgage Securitization, Journal of Financial Economics, 105(3): 640-660; Rajan, U., A. Seru, and V. Vig,2015, "The Failure of Models that Predict Failure: Distance, Incentives, and Defaults," Journal of Financial Economics, 115(2): 237-260.

("binomial logit" model) and then convert them to multinomial logit probabilities.[145] Using binomial logits reduces the computational complexity compared to a multinomial logit where all outcomes are estimated simultaneously. Logit models are easy to estimate, implement and interpret. However, one drawback of these models is that they assume that every observation of a given loan is independent ("serial independence"); if specific loans have unobserved differences that increase or decrease their default or prepay risk, these differences will not be accounted for in the model.

An alternative approach to modeling mortgage default and prepayment is a proportional hazard model approach, where for each quarter, the probability of a loan reaching default or prepayment in that quarter is estimated, given that default or prepayment was not reached in a previous quarter. Starting with Deng, Quigley, and Van Order, (2000)[146], hazard models with competing risks have become widespread in academic research.[147] Compared to logit models, hazard models effectively deal with unobserved heterogeneity across loans, as they relax the assumption of serial independence. However, hazard models simply provide the likelihood of reaching the outcome states (in this case, prepay or default) in each quarter; they do not output the progression of loans between various states of delinquency. This progression is important for use in a supervisory stress test context, where the scenario variables vary in each quarter and can

[145] Begg, C.B., R. Gray, 1984, Calculation of polychotomous logistic regression parameters using individualized regressions, Biometrika, 71: 11-18.
[146] Deng, Y., J.M. Quigley and R. Van Order, 2000. Mortgage Terminations, Heterogeneity and the Exercise of Mortgage Options, Econometrica, 68(2): 275-307.
[147] *See* Calhoun, C.A. and Y. Deng, 2002. A Dynamic Analysis of Fixed- and Adjustable-Rate Mortgage Terminations, The Journal of Real Estate Finance and Economics, 24(1-2): 9-33; Deng, Y. and J.M. Quigley, 2002. Woodhead Behavior and the Pricing of Residential Mortgages, USC Lusk Center for Real Estate Working Paper, No. 2001-1005; Pennington-Cross, A., 2003. Subprime and Prime Mortgage: Loss Distribution, OFHEO working paper 03-1; Deng, Y. and S.A. Gabriel, 2006. Risk-Based Pricing and the Enhancement of Mortgage Credit Availability among Underserved and Higher Credit-Risk Populations, Journal of Money, Credit and Banking, 38(6): 1431-1460; Gerardi, K., A. H. Shapiro and P. S. Willen, 2007. "Subprime Outcomes: Risky Mortgages, Homeownership Experiences and Foreclosures," Federal Reserve Bank of Boston Working Paper 07-15.

impact loans differently depending on where in the delinquency process they are at any given point in time. For instance, the impact of a sharp decline in house prices in a quarter may be different for loans that have become delinquent in a previous quarter, compared to loans that are current in that quarter. The structure of the hazard model does not easily allow for this effect to be captured.

A state transition model framework, as used in the First Lien PD model, resolves the issue of tracking progression of individual loans, relaxing the assumption of serial independence. This is generally implemented using a Markov chain framework, where loans are probabilistically assigned to each state in each quarter. The state transition model framework consists of equations, such as binomial or multinomial logits, that predict the probability of transitioning from one state to another state, given the starting state. Examples of state transition models in academic literature include Betancourt, (1999)[148]. Outside of academia, state transition models have wide use; see industry examples such as Bergantino and Li, (2010);[149] or government applications such as the Department of Housing and Urban Development's Mutual Market Insurance Fund.[150]

State transition models perform well when extensive data are available and computational power is available (state transition models are computationally complex). One drawback of state transition models relying on Markov chains is that they generally only consider the current state in determining transition probabilities; in reality, the loan's history might be relevant. For instance, a loan with previous delinquency history may be more likely to fall back into

[148] Betancourt, L., 1999. Using Markov Chains to Estimate Losses from a Portfolio of Mortgages, Review of Quantitative Finance and Accounting, 12(3): 303-317.
[149] Bergantino, S. and C. Li, Barclays Capital Loan Transition Model, Barclays Capital Securitization Research (Nov. 30, 2010).
[150] Annual Actuarial Review of the FHA Mutual Mortgage Insurance Fund Forward Loans – Fiscal Year 2024. United States Department of Housing and Urban Development, (November 13, 2024), https://www.hud.gov/sites/dfiles/Housing/documents/2024-MMI-Forward-Loans-Final-Report.pdf.

delinquency, even if the loan is current at a given point. While there are ways to address this limitation, the Board tested the inclusion of previous delinquency in the model and found that the inclusion of this term would have a minimal impact on projected loss rates at the firm level. Given this finding, it is unlikely that failing to account for historical delinquency notably reduces model accuracy or impacts firm stress test results.

One paper by Hale, Krainer, and McCarthy (2020)[151] compares model projections using variations of loan-level, bottom-up models (based on binomial logit structures) to "top-down" models that aggregate loans prior to making projections. In particular, the top-down model approach estimates two models where the default rate in a given quarter is based on average loan characteristics and macroeconomic variable values, aggregated to the county and national levels, respectively. The paper concludes that the performance of aggregated models can exceed that of loan-level models, although the optimal level of aggregation may vary based on characteristics of the data and of the portfolio.

In addition to model structure, literature review also provides evidence supporting identification of the variables that are most important in determining default and prepayment risk. As noted earlier, the amount of home equity available to a borrower (referred to as the mark-to-market loan-to-value or refreshed loan-to-value) is a key factor in predicting nonpayment. This has been confirmed by studies such as Bajari, Chu, and Park, (2008)[152]; Foote, Gerardi, and Willen, (2008)[153]; and Haughwout, Peach, and Tracy, (2009). Due to falling home values during the 2008 financial crisis period, there was significant focus in these years to

[151] Hale, Galina, John Krainer, and Erin McCarthy. "Aggregation Level in Stress-Testing Models." International Journal of Central Banking 16, no. 4 (2020): 1-46 conclude that segment level models can produce robust results.
[152] Bajari, P., C.S. Chu, and M. Park (2008), "An Empirical Model of Subprime Mortgage Default From 2000 to 2007," NBER Working Paper #14625.
[153] Foote, C., K, Gerardi, and P. Willen (2008), "Negative Equity and Foreclosure: Theory and Evidence," Journal of Urban Economics 64, Number 2, 234-245.

identify the causes of mortgage defaults. Other economic factors also influence default risk. For example, Bhutta, Dokko, and Shan, (2010)[154] distinguish between defaults induced by job losses and other income shocks from those defaults induced purely by negative equity, and they find that both LTV and job loss play an important role in mortgage defaults. Based on these papers as well as independent analysis, the Board includes measures of both updated LTV and proxies for job loss (via unemployment rates) in the First Lien Model.

Credit scores are another useful predictor used in the First Lien Model after surveying the literature. Elul (2009) finds that low credit score borrowers have higher risk of becoming delinquent; the paper notes that credit scores have a greater impact on subprime low-doc delinquency rates than they do on similar full-doc loans. [155] The score generally reflects the overall credit performance of a borrower—if a borrower becomes past due on any of his loan obligations or becomes credit constrained, it is reflected in his credit score, which allows banks to differentiate borrowers of different creditworthiness and is a strong indicator of future default. Krainer and Laderman (2011) find that borrowers with low credit scores experienced a relatively larger increase in mortgage defaults during the financial crisis period. [156] Overall, these results confirm the importance of debt burden, equity position, income uncertainty, and credit scores in assessing the risk of mortgage defaults.

Interestingly, a number of published papers have identified that while borrowers with higher origination credit scores are less likely to default, they are more likely to default conditional on becoming delinquent; in other words, higher credit score borrowers have lower

[154] Bhutta, N., J. Dokko, and H. Shan (2010). "The Depth of Negative Equity and Mortgage Default Decisions," Federal Reserve Board Working Paper.
[155] Elul, R. (2009). "Securitization and Mortgage Default: Reputation vs. Adverse Selection," Federal Reserve Bank of Philadelphia, Working Paper No. 9-21.
[156] Krainer, J. and E. Laderman (2011). "Prepayment and Default in the Mortgage Crisis Period," Federal Reserve Bank of San Francisco Working Paper.

cure rates than lower credit score borrowers. See, for example, Adelino et al. (2013).[157] Liu and Tien (2018)[158] find that subprime borrowers with underwater fixed-rate mortgages have higher cure rates, although the same is not found for ARMs. The model used by the Department of Housing and Urban Development's Mutual Market Insurance Fund, referenced earlier in this sub-section, shows cure rates are lower for high and low credit score borrowers compared to borrowers with middling scores; the 2024 actuarial review (ITDC, 2023-2024)[159] indicates that cure rates are highest for borrowers with credit scores around 660. The finding that higher credit scores are associated with lower cure rates align with observed findings in the First Lien Model, as indicated by the coefficients in Table C2 and Table C4. These findings suggest that while low credit score borrowers may fall into and out of delinquency, a high credit score borrower who enters delinquency likely has experienced a substantial shock which cannot be easily reversed.

While these variables are of particular focus in the literature, many other variables are noted as relevant in determining mortgage default. Discussion of all such variables is available in this section, separately for variables included in the model (see Section C.ii.a.(2)) and for variables considered but ultimately not included in the model (see Section C.ii.a.(4)).

This, as well as other important mortgage literature, provides the basis for the development of the First Lien PD Model. This important academic research was paired by independent analysis and review of the input data to determine the appropriate model for use in the supervisory stress test.

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157 Adelino, M., K. Gerardi, and P.S. Willen, 2013, Why Don't Lenders Renegotiate More Home Mortgages? Redefaults, Self-cures and Securitization, Journal of Monetary Economics, 60(7):835-853.

158 Liu, B. and F.S. Tien, 2018, "Cure" Effects and Mortgage Default: A Split Population Survival Time Model, Journal of Real Estate Finance and Economics, 56(2): 217-251.

159 IT Data Consulting (ITDC), 2023-2024, Independent Actuarial Review of the Mutual Mortgage Insurance Fund, Report for the U.S. Department of Housing and Urban Development.

Support for Model Design

The First Lien PD Model uses a loan-level, state transition model approach, where loans are defined in each period into one of many (in this case, four) possible payment statuses and the equations in the model are used to indicate the probability of a loan in one state transitioning to another state. To reach default, a borrower must fall into delinquency, then may remain in delinquent status, receive a loan modification, self-cure this delinquency, or default. As noted in the review of the literature, the transition model is common throughout academic literature and has been applied in industry and government settings as well. While other model structures, such as a proportional hazard model as discussed in "Review of Literature," can estimate default and prepayment risk at the loan level, the transition model's ability to capture the flows between intermediate and final payment statuses during the projection period make it particularly well-suited for use in the stress testing context. This is particularly valuable in cases where a significant share of loans are delinquent at the start of the projection horizon, as the model is able to take into account the starting delinquency status when projecting PD. Other advantages of this approach relative to others are discussed above.

The First Lien PD Model projects losses on both ARMs and FRMs. The framework for modeling these products is identical, reflecting that despite differences in interest rate behavior, the two product types are broadly related. However, while the modeling framework is consistent, FRMs and ARMs are modeled using separate equations, due to fundamental differences between the products. Notably, scheduled ARM payments vary with market interest rates, while FRMs have consistent, predictable payments throughout the term of the loan. This leads to differences in the behavior of the two products, particularly around the time where the

ARM rate first resets,[160] when both default and prepayment are more likely. Due to these differences, the exact loan, borrower, and macroeconomic characteristics that are predictive of default can vary between the products. The variables used in each transition equation are explained in detail in "Support for Variables and Transformations Included in the Model."

The four payment statuses used in the model are defined to be consistent with industry definitions and to be reflective of the most economically important features of loan performance. The 180-day trigger used to define loans as in default, described in the introduction to Section C.ii, is intended to be consistent with the Federal Financial Institutions Examination Council (FFIEC) Uniform Retail Credit Classification and Account Management Policy,[161] which states the following:

> For open- and closed-end loans secured by one-to four-family residential real estate, a current assessment of value should be made no later than 180 days past due, and any outstanding loan balance in excess of the value of the property, less cost to sell, should be charged off.

The other default conditions used in the model (detailed earlier in Section C.ii.a.(1)) are associated with clear evidence that the loan was terminated and not repaid in full. Once the loan is marked as involuntarily liquidated or the collateral is repossessed, the chance for the borrower to cure the default has passed, regardless of the number of days delinquent.[162]

The model defines loans as delinquent if they are 90-179 days past due or in foreclosure proceedings. This is consistent with other applications that treat a loan that is three or more

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[160] ARMs often have a fixed interest rate period at the beginning of the term; after a period of time laid out in the contract (often 3, 5, 7, or 10 years), the rate begins to adjust.
[161] Federal Financial Institutions Examination Council. Uniform Retail Credit Classification and Account Management Policy, (June 12, 2000), https://www.federalregister.gov/documents/2000/06/12/00-14704/uniform-retail-credit-classification-and-account-management-policy.
[162] In certain states, borrowers have a "right of redemption" that allows them to keep or regain their properties even after liquidation. In this case, redemption involves paying off the loan balance in full. The Board does not explicitly model the probability that a borrower will exercise their right of redemption; however, this possibility is implicitly captured via the probability that the LGD of a loan (based on the model described in Section C.ii.b) is zero.

months behind on payments as seriously delinquent.[163] Loans in foreclosure are marked as delinquent to reflect that the loan is sufficiently delinquent for the lender to begin foreclosure proceedings.

Loans are treated as defaulted if they meet the default criteria in any month within a quarter. Similarly, loans are treated as delinquent if they meet the delinquent criteria in any month in the quarter, unless they meet the default criteria or were paid off during that same quarter. This is in line with the stress testing principle of conservatism, as it ensures that delinquencies and defaults, respectively, are accounted for even if the conditions are only triggered at an intermediate point during the quarter.

The model defines loans as paid off based on a flag available in the First Lien PD Data. This is simply defined as a loan which has been paid off in full by the borrower.

The model defines loans as current if they are not paid off and do not meet the definitions of default or delinquent. In practice, this means that active loans with positive balance that are less than 90 days past due and not in foreclosure proceedings are treated as current.

The definitions of current and delinquent in the model are relatively broad; these broad definitions simplify the modeling approach by not treating early-stage delinquency (30-89 days past due) loans as different from loans that have not missed any payments, and by treating all severe delinquencies (90-179 days past due) similarly. While this assumption inhibits the model's ability to differentiate the risk of loans based on a more granular definition of delinquency status, it simplifies the modeling approach by limiting the number of payment statuses and transition equations in the model. Using these definitions is also consistent with the

[163] "Household Debt Balances Continue Steady Increase; Delinquency Transition Rates Remain Elevated for Auto and Credit Cards," Federal Reserve Bank of New York, (13 Feb. 2025), https://www.newyorkfed.org/newsevents/news/research/2025/20250213.

quarterly macroeconomic scenario data applied to the model to produce loss rates in the supervisory stress test, as 90 and 180 days are associated with the elapse of one and two quarters, respectively.

Additionally, the model identifies loans that transfer servicers (often due to a sale of portfolio loans) in a given quarter. When a loan transfers servicers, it generally cannot be tracked across servicers in the First Lien PD Data. The Board does not model the likelihood of a loan transferring servicers, as firms may retain credit risk on loans even after transferring their servicing rights. The choice not to model the likelihood of a loan transferring servicers is also consistent with the constant balance sheet assumption used across the supervisory stress test models, which states that firm balance sheets should be assumed to remain constant through the projection horizon. Due to data censoring in the First Lien PD Data after the transfer date, and due to the decision not to explicitly model the probability of a loan transferring servicers, loans that transfer servicers are removed from the data beginning in the period of the transfer.

The model calculates the probability of loans transitioning between many of the identified aforementioned payment statuses. In particular, the model allows current loans to remain current or transition to the delinquent or payoff payment statuses, while delinquent loans can remain delinquent or transition to current, payoff, or default. A key assumption implicit in the model structure is that certain transitions are not possible, as described below:

- Current loans cannot directly transition to default. This is a natural result of the model's definition of current loans as less than 90 days past due, and defaulted loans as greater than 180 days past due. Due to these definitions, the model assumes two quarters are needed for a loan to transition from current to delinquent to default. In extremely rare circumstances, covering approximately 0.01 percent of observations in the data used to calibrate the model coefficients ("estimation data"), loans do transition directly from current to default. However, in line with the principle of simplicity from the Stress Testing Policy Statement, the Board does not model this extremely rare transition; the Board tested allowing loans to transition directly from current to default and found that projected loss rates were unchanged. In the estimation data, when loans transition directly from current to default (for instance, if the loan was liquidated or prepaid with loss prior to reaching 180+ days of delinquency), the Board removes such observations from the estimation sample.

- Default and payoff are considered to be "terminal" payment statuses in the model; loans are not able to transition from these payment statuses to other statuses. In the case of payoff, this is straightforward, as once the loan has been paid off, the loan is no longer active and has no balance; a loan reported to be paid off in one quarter and then a different status in the next quarter would be presumed to be a data error. In the case of default, the model does not allow loans that have reached 180+ days past due to cure and return to a different status. While cures from 180 or more days past due are observed in the historical data, they are rare, accounting for less than five percent of defaulted loans, as it is uncommon for borrowers who have reached such a severe stage of delinquency to return to making regular payments. Additionally, not allowing for default cures removes the need to estimate an additional transition equation in the model. An additional equation would increase the complexity of the model, and would be challenging to fit given how infrequent cures are in the historical data, potentially leading to imprecise projections. Finally, treating default as a terminal status is aligned with the stress testing principle of conservatism. While allowing loans to cure from default would reduce probability of default, and therefore losses, on first lien mortgages, this could lead to inappropriately low loss projections if, as is likely, fewer loans cure during a period of housing market stress. Finally, this is in line with the FFIEC Uniform Retail Credit Classification and Account Management Policy, which requires lenders to charge off projected losses at least by this point. The ability of loans to default without loss is captured in part by the possibility that the projected LGD of a loan (as described in Section C.ii.b) can be zero.

The system of equations used in the model produces the probability that a loan in a given state transitions to a different state over a given quarter. Once a loan reaches a terminal state, it is assumed to remain in that state through any future periods projected by the model.

Since default is treated as a terminal state in the model, loans that enter the projection period in defaulted status are not run through the equation framework. Instead, this balance is tracked separately, and losses on defaulted loans are assumed to be spread evenly across the first six projection quarters. Spreading losses on loans starting in default avoids the loans from all being charged off at once at the start of the projection, which would create unreasonably high provision estimates. The Board determined that a six-quarter smoothing period was appropriate to balance the principle of conservatism, which indicates that defaulted loans should be charged off expeditiously to avoid delaying the realization of imminent loan losses, while avoiding the creation of an artificial bunching effect from assuming all existing defaults will be charged off simultaneously. Additional support for this assumption is available in Section C.ii.d.

Certain first lien portfolio loans, namely FHA Residential, VA Residential, FHA Project, and HUD 235 loans,[164] are insured by the government. Since insurance covers some or all of the losses on these loans, the model does not apply losses to government-insured loans. Additional information about the treatment of government-insured loans is available in Section C.ii.d.

Support for Variables and Transformations Included in the Model

With the overall model structure defined, the variables used in the individual equations are discussed. To ensure the model is appropriately sensitive to the different indicators of default risk, the Board considered a wide range of variables for inclusion, covering characteristics of the loan and the borrower as well as macroeconomic conditions. Loan and borrower characteristics are sourced from the First Lien PD Data to produce the model parameters and coefficients and from the FR Y-14M report to produce PD projections. Macroeconomic conditions are included, as described in this model description. From this wide range of variables, the final variables included in each of the 10 transition equations are chosen based on the Board's assessment of economic support, statistical fit, and in certain cases, data availability.[165]

The variables included in each transition equation, and across equations of each product type, are chosen independently. While in many cases different characteristics across product type and across different transitions within a given product type justify the inclusion of different

[164] As reported on FR Y-14M, Schedule A.1, Line Item 16 ("Loan Type").
[165] Because the First Lien PD Data are used to produce the model parameters, variables used in the model are limited to those that can be observed in that dataset as well as the FR Y-14M. While there is substantial overlap between the variables in the two datasets, there are some exceptions, and in certain cases coverage of a variable in the historical First Lien PD Data is limited, making it challenging to include that variable in the model. See Section C.ii.a.(4) for more details.

variables, the Board seeks consistency where possible. This is consistent with the stress testing principle of consistency, and improves the interpretability of the model as it reduces the number of defined variables, and also simplifies the data cleaning and processing needed to run the model as it minimizes the number of terms that must be defined.

Economic support and statistical fit are used to support many of the variables included in the model. The first step of establishing economic support is to qualitatively assess, based on a survey of the relevant literature (see "Review of Literature") and expert judgment based on the Board's experience and expertise, the most important drivers of transitions in the model. Relying on these factors to determine the set of variables considered for inclusion limits the risk of over-fitting, which could lead to inaccurate projections. The Board uses this qualitative assessment to predict the relationship between a given input variable and outcome variable (in this case, the probability of a loan transitioning to a different state). With that determined, the Board estimates a model, and based on the model estimates considers whether the sign of the coefficient on the variable is consistent with expectations. For instance, higher credit scores are associated with lower odds of nonpayment, so the coefficient on credit score in the current-to-delinquent transition should be negative. If the sign of the variable in the resulting equation does not align with expectations, the Board would assess further and determine the reason. Additionally, if a coefficient does have the expected sign but does not have an empirically important relationship with the outcome variable, the Board may exclude the variable from an equation to reduce model complexity, in line with the stress testing principle of simplicity.

Statistical fit is assessed based on tests of statistical significance and in-sample and out-of-sample fit. The Board tests for statistical significance via standard statistical tests and then uses measures of in-sample and out-of-sample fit further bolster statistical fit. The Board assesses in-sample and out-of-sample fit by using the model estimates to project each transition probability and then assessing whether these projected probabilities are reasonably comparable to actual probabilities. For instance, if a certain portion of loans or loans in a particular macroeconomic environment are consistently assigned projected probabilities substantially above or below the actual probabilities, this would suggest that a variable is missing or poorly specified and an adjustment to the model specification could improve the quality of the model. Consistent with the Stress Testing Policy Statement's discussion of the importance of evaluating the impact of severe economic stress, the Board pays particular attention to situations where the specification appears to produce inaccurate projections for loans in periods of severe economic stress, such as during the 2008 financial crisis.

Variables with an interpretable economic relationship with the likelihood of a given transition that enter the relevant equation with an appropriate sign, statistical significance, and sufficient magnitude to be economically important are included in the final model. Whether a variable's inclusion meaningfully improves the ability of the model to predict outcomes for a certain subset of loans bolsters the statistical case for its inclusion.

For more common transition equations, the sample size is larger, allowing for the inclusion of more terms in the model while maintaining economic support and statistical fit in all cases. In less common transition equations, particularly the transitions from delinquent, this is more challenging; as a result, fewer variables are included in these equations.

The Board considers additional factors as well. Implementation feasibility is considered, as the variables applied in the model must be projected over the 13-quarter period used to produce estimates of loan losses and allowances. Simplicity is considered as well, consistent with the Stress Testing Policy Statement. If a more complex specification of the model (for instance, more variables) has minimal impact on model performance compared to a simpler specification, the simpler specification is used. Finally, for situations where the aforementioned factors of economic support, statistical fit, and implementation feasibility do not clearly point to a single option, the Board's decisions reflect the principle of conservatism.

Certain variables in the model use linear splines to account for non-linear effects. These non-linear effects are set at discrete locations, known as "knots," as described in Section C.ii.a.(1). These knots are identified based on Board experience and expertise, including industry knowledge and review of literature; the Board selects final knots for individual variables in individual equations based on statistical fit.

The rest of this section discusses how the above principles are applied to create each of the individual transition equations. A further discussion of alternative variables not included in the model is available later in Section C.ii.a.(4). For each of the variables, the variable is described, and the interpretation of its impact based on its coefficient in Tables C1 – C4 is described. In cases where analysis of the coefficients is bolstered with support from the literature or supplementary analysis, this additional support is described as well.

FRM, Current-to-Delinquent

- Origination credit score (knots at 700 and 780): As credit score increases, the likelihood of delinquency falls, as observed in Krainer and Laderman (2011). Board analysis of First Lien PD Data shows that this effect is non-linear; relative risks of becoming delinquent decrease faster for credit scores above 700 and again above 780, as demonstrated by the negative coefficients on these two knots. Note that the model assigns a value of "0" in the credit score field when it is missing and applies a flag to identify loans with missing credit scores to separately assess the risk of loans missing credit scores. When using the model to project default rates, the Board does not apply this variable; instead, the Board imputes the industry 10th percentile credit score as described in Section C.ii.a.(3).
- Industry COVID-19 forbearance rate: During the COVID-19 pandemic period, forbearance programs and other government support programs reduced the cost of nonpayment to borrowers, increasing delinquency rates observed in the First Lien PD

Data during this period.[166] This term is set equal to the share of portfolio loans[167] at large banks[168] that were in COVID-19 forbearance programs in a given quarter, and is used to proxy for the distortions to the mortgage market observed during the pandemic period. This share is calculated for periods between the second quarter of 2020 and the third quarter of 2022 (the last period used in model estimation) and is set to 0 for periods prior to April 2020. This share is assumed to be 0 for all loans when using the model to project PD, as COVID-19 forbearance programs have since ended.

- GSE repurchase flag: The GSE repurchase flag is set to 1 for portfolio loans that were at some point in the previous year marked as being owned by Fannie Mae or Freddie Mac, and have since returned to the firm's balance sheet. In the FR Y-14M data, this is assessed based on a value of "2" (Fannie Mae) or "3" (Freddie Mac) being reported in FR Y-14M, Schedule A.1 (First Lien), Line Item 50 (Investor Type). Generally, loans are repurchased from GSEs when they have underwriting defects. Since repurchases are generally made due to underwriting defects, these loans are riskier and more likely to go delinquent, as observed based on the positive coefficient on this variable. GSE repurchases are discussed in further detail in Section C.ii.a.(3).
- Change in unemployment rate over previous year: Academic literature, such as Elul et al. (2010),[169] demonstrate the importance of "double trigger" in predicting mortgage delinquency. The double trigger refers to the joint shocks to home equity (driven by falling home prices) and liquidity (driven by income loss); both factors are often needed to cause default. The change in unemployment rate proxies for the liquidity shock. While the model does not observe individual income levels, increases to state-level unemployment rate are predictive of income loss among borrowers in that state. Increases in unemployment rate are associated with increased delinquency, as observed in the coefficient on this variable.
- Change in house price index (HPI) over previous year: House price index is a measure of the level of house prices. Increases in HPI reflect appreciation, while decreases in HPI reflect house price decline.[170] House price changes are the other portion of the double trigger described in the previous bullet. House prices enter the equation both directly in this term as well as via the updated LTV calculation. Empirically, as the coefficient on this variable demonstrates, year-over-year changes are predictive of delinquency, keeping updated LTV constant.
- Interest only indicator: This term identifies loans where the borrower is required to only make interest payments (as opposed to interest and principal payments) at origination. Borrowers with interest-only loans are riskier than borrowers with amortizing loans as observed historically in the First Lien PD Data during the 2008 financial crisis.
- Origination year (each year of 2006-2011 and a single flag for 2012 and later): These variables capture underwriting changes that are not captured by the observable variables.

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[166] The Board's definition of delinquency relies on the time elapsed between the payment due date and the current time period, regardless of forbearance status. Therefore, the model assesses loans in forbearance as delinquent or in default if sufficient payments are missed, regardless of forbearance status.

[167] "Portfolio" loans are defined in Section C.ii.a.(3).

[168] *See* Section C.ii.a.(3). The term "large banks" is based on definitions provided by the data vendor.

[169] Elul, R., N. S. Souleles, S. Chomsisengphet, D. Glennon, and R. Hunt (2010). "What 'Triggers' Mortgage Default?" American Economic Review Papers & Proceedings 100(2): 490-94.

[170] *See* Section C.ii.a.(3) for details on the assignment of house price index to each loan.

The 2006-2008 vintages are the "bubble vintages" and have higher delinquency rates than the 2002-2005 base vintages, whereas 2009-2011 and 2012+ vintages are post-crisis vintages under tighter underwriting standards and thus are less likely to become delinquent than the 2002-2003 base vintages. These coefficients reflect the estimated parameters based on historical data. When using the model to project PD, however, the model treats loans originated in or after 2009 as having the risk level of loans originated prior to 2006; essentially, less risky than the "bubble vintages" but riskier than the coefficients on the post-crisis coefficients would indicate. This assumption is aligned with the stress testing principle of conservatism, due to uncertainty in the true risk level of recent originations. While some risk factors, such as underwriting quality, have improved since the period before the financial crisis, other risk factors, such as the propensity to engage in fraud[171] or borrowers de-prioritizing mortgage payments compared to their other liabilities,[172] could likely return during another downturn in the housing market. Furthermore, some of those changes in borrower behavior (such as payment prioritization) are based on future expectations in housing price movements and cannot be effectively accounted for using contemporaneous housing prices. Given that vintages in and after 2012 have not been exposed to a housing downturn, the Board believes that these coefficients may be imprecisely estimated, further motivating a conservative approach. One marker that indicates that recent vintages may be riskier than anticipated is that debt-to-income ratios have increased from their lows in the early 2010s, based on Board review of historical FR Y-14M data.

- Jumbo loan interaction with origination year: The model includes interactions between the post-2006 vintage dummies and the jumbo loan indicator.[173] This accounts for differences in behavior among loans that are too large to be eligible to be sold to GSEs. Following the 2008 financial crisis, as private label securities became less widespread, the risk levels of jumbo loans shifted. Similar to the origination year variables, 2009 and after vintages are treated similarly to pre-bubble vintages. In this case, the impact of this assumption is small, as the interaction between jumbo loans and post-2012 originations has a coefficient that is close to zero.
- Loan age (knots at 12 and 24 months): Loan age terms capture the increasing delinquency risk of loans due to seasoning (meaning the amount of time a borrower has held a loan) as well as the impact from amortization. The risk of becoming delinquent increases over the first year after origination, before leveling out and then beginning to decline slightly after two years, as observed based on the coefficients on these terms.
- Retail indicator: Loans that were originated in the retail channel tend to be less risky since the seller/servicer controls the underwriting, as indicated based on the negative coefficient on this variable.

[171] Occupancy fraud was widespread during the great financial crisis period and remains a potential risk in recent periods. Elul, R., A. Payne, and S. Tilson, 2023, "Owner-Occupancy Fraud and Mortgage Performance," Real Estate Economics 51(5): 1137-1177.

[172] There is historical evidence that borrowers deprioritize mortgage payments during a housing downturn. See Conway, J., N. Fischl-Lanzoni, and M. Plosser. "When the Household Pie Shrinks, Who Gets Their Slice?" Federal Reserve Bank of New York, (6 March 2025), https://libertystreeteconomics.newyorkfed.org/2025/03/when-the-household-pie-shrinks-who-gets-their-slice/.

[173] Jumbo loans are defined as loans whose origination amounts exceed the maximum baseline loan amount for their respective number of units as reported by GSEs in the origination year.

- Origination spread (knots at 1 percent and 3 percent): The origination spread is calculated as the difference between the origination interest rate and the 10-year Treasury yield at origination. A higher spread at origination indicates that the lender required a higher interest rate to cover otherwise unobserved risk. While the origination spread is predictive of delinquency for the bulk of loans, extreme cases are idiosyncratic, and therefore the model uses spline knots to reflect that marginal impacts are lower at the extremes.
- Loan term: Loans with less than 30-year terms are generally less risky, as indicated by the negative coefficient on this variable.
- Updated LTV: This is an important determinant of delinquency, consistent with the literature referenced in "Review of Literature." As described previously, updated LTV is calculated as the origination LTV divided by appreciation since origination. Updated LTV is grouped into buckets to reflect changing impacts of LTV on non-payment risk at different points in the distribution. The following buckets are used in the model: [0,50), [50,60), [60,70), [70,80), [80,90), [90,100), [100,110), and [110,130); coefficients reflect risk compared to that of a loan with LTV greater than 130. The large number of buckets were chosen to granularly assess the impact of changes in updated LTV on the likelihood of becoming delinquent; the Board determined that a larger number of buckets risked creating spurious coefficients, while a smaller number of buckets risked failing to account for true differences in non-payment risk across loans. In general, these coefficients demonstrate that loans with lower updated LTV have lower risk of transitioning to delinquency. For discussion of the impacts of not considering amortization in this calculation, see Section C.ii.a.(4).

FRM, Current-to-Payoff

- Origination credit score (spline at 660): There is a weak, positive relationship in the historical First Lien PD Data between credit score and refinance frequency, as observed by the positive coefficient on this variable. Borrowers with higher credit scores are more likely to get approved for a refinance. The model also includes a dummy for missing credit score at origination. Note that the model assigns a value of "0" in the credit score field when it is missing and applies a flag to identify loans with missing credit scores to separately assess the risk of loans missing credit scores. When using the model to project default rates, the Board does not apply this variable; instead, the Board imputes the industry 10^{th} percentile credit score as described in Section C.ii.a.(3).
- GSE repurchase flag: As defined in "FRM, Current-to-Delinquent." Generally, loans repurchased from GSEs are more likely to payoff than other loans, based on the positive coefficient on this variable.
- Change in HPI over previous year: Borrowers tend to be more likely to pay off their loans in appreciating housing markets, as observed by the positive coefficient on this variable.
- Loan age (knot at 12 months): Analysis of First Lien PD Data shows that payoff rates increase rapidly for the first twelve months after origination; however, after that, the relationship flattens out.
- Loan term: Loans with terms less than 30 years have a higher propensity to pay off, as demonstrated by the positive coefficient on this variable.

- Updated LTV: As defined in "FRM, Current-to-Delinquent." Updated LTV is grouped into buckets to reflect changing impacts of LTV on non-payment risk at different points in the distribution. In general, loans with lower updated LTV are more likely to prepay, particularly for loans with a mark-to-market LTV less than 80 percent (based on the coefficient estimates in Table C1). This is consistent with the expectation that borrowers need a sizable equity cushion to fully exercise most prepayment options, but beyond that there is only minimal impact of increasing equity. The following buckets are used in the model: [0,50), [50,60), [60,70), [70,80), [80,90), [90,100), [100,110), [110,130), and [130,150). The large number of buckets were chosen to granularly assess the impact of changes in updated LTV on the likelihood of payoff; the Board determined that a larger number of buckets risked creating spurious coefficients, while a smaller number of buckets risked failing to account for true differences in payoff likelihood across loans. Each of the coefficients compares the likelihood of payoff compared to an equivalent loan with updated LTV above 150.
- Burnout: Hall (2000)[174] and others note that certain loans pay off more slowly than expected due to factors not otherwise captured in the models. To capture this 'burnout' effect, the model includes a simple measure of previous opportunities to refinance by comparing the fixed mortgage rate (denoted by time t=0) against mortgage rates prevailing over the life of the loan (denoted by time t=k). A larger "burnout" is indicative of the borrower having turned down previous chances to prepay even when refinance appears rational, suggesting the borrower has an otherwise unobservable lower propensity to prepay. The negative coefficient on the burnout variable captures this effect when time k rates decline below the FRM rate and borrowers fail to exercise their option to prepay. Mathematically, this term can be denoted as:

Equation C4 - Burnout

$$Burnout_{i,t} = \sum_{k=0}^{t} \max\left(\log\left(\frac{MortRate_0}{MortRate_k}\right), 0\right).$$

- Seasonality indicator (Q1 and Q2): As demonstrated by the coefficients on these variables, higher payoff rates are observed in the first two quarters of the year. Note that due to the way the model is specified, the indicator variables for the quarters are associated with the likelihood that a loan that is active in a given quarter will pay off in a future quarter; for instance, the Q1 indicator reflects the likelihood that a home will be paid-off over the second calendar quarter. The Q1 and Q2 indicators therefore cover payoffs that occur between April and September. The observed higher prepayments in these quarters is consistent with traditional patterns of seasonality in mortgage prepayment. Per the National Association of Realtors, "home sales in the winter months are generally much slower than sales in the summer months, primarily because of differences in weather;" [175] these two quarters fully encompass these summer months. As

[174] Hall, Arden (2000). "Controlling for Burnout in Estimating Mortgage Prepayment Models," Journal of Housing Economics, 9(4): 215-232.
[175] "Methodology: Existing-Home Sales." National Association of Realtors, https://www.nar.realtor/research-and-statistics/housing-statistics/existing-home-sales/methodology.

home sales are generally lower in other months, the model does not differentiate the likelihood of payoff between the two other quarters.

- Loan size (log) (knot at $60,000): The Board determined based on analysis of First Lien PD Data that prepayment rates first decrease, then increase with loan size as the refinance incentives and ability to pay off the loan change with loan size; this is confirmed based on the negative coefficient on loan size paired with the positive coefficient on the knot at $60,000. The log specification is used commonly in statistical models. Using the log of loan size is approximately equivalent to assuming that constant percentage changes in loan size will have constant effects (i.e. a 3 percent increase in loan size will always impact the model similarly).
- Investment indicator: Loans secured by investment properties are less likely to be refinanced, as indicated by the negative coefficient on this variable.
- Secondary residence flag: Loans secured by second homes are less likely to be refinanced, as indicated by the negative coefficient on this variable.
- Pre-2003 origination indicator: Loans originated in 2002 were more likely to prepay during the 2003 refinance wave; those that did not prepay during the wave are a selected subset of those loans which did not retain the rapid prepayment rates of 2002-2003. This explains the positive coefficient on this term as well as the negative coefficient on the "pre-2003 origination after 2003 indicator" described below.
- Pre-2003 origination after 2003 indicator: As stated in the previous bullet, loans originated in 2002 were more likely to prepay during the 2003 refinance wave; those that did not prepay during the wave are a selected subset of those loans which did not retain the rapid prepayment rates of 2002-2003.
- Refinance incentive (knot at 1 percent): Refinance incentive is defined as the difference between the average 30-year fixed-rate mortgage rate at origination compared to the value in a given time period. This is arguably the most important determinant of payoff, as borrowers have a strong incentive to refinance when rates have dropped from their origination levels.[176] There is a strong, positive relationship between decreasing interest rates and increasing prepayment; however, as indicated based on the coefficients on these variables, after interest rates have dropped by more than one percentage point, the additional impact of further rate declines are less important.
- Yield curve spread (10-year Treasury minus 3-month Treasury): A steeper yield curve is correlated with lower prepayment rates of FRMs, as demonstrated in the negative coefficient on this variable in Table C1. This is consistent with an expectation that paying a higher premium on long term debt relative to short term debt, all else equal, decreases the net present value of refinancing relative to other short-term opportunities.

FRM, Delinquent-to-Current

- Change in HPI over previous year: Rising house prices increase the likelihood of curing, as observed based on the positive coefficient on this variable.
- Origination credit score (spline at 720): As described in "Review of Literature," the model coefficients show that, consistent with studies such as Adelino et al. (2013) and ITDC (2023-2024), loans with higher origination credit scores are more likely to default

[176] *See*, *e.g.* Calhoun and Deng (2002).

and less likely to cure. While higher credit borrowers are less likely to go initially delinquent, when they do it is generally for some sustained shock, like unemployment or loss of income, making them less likely to cure. Note that the model assigns a value of "0" in the credit score field when it is missing and applies a flag to identify loans with missing credit scores to separately assess the risk of loans missing credit scores. When using the model to project default rates, the Board does not apply this variable; instead, the Board imputes the industry 10th percentile credit score as described in Section C.ii.a.(3).

- Loan size (log): Borrowers with larger loan amounts tend to be more likely to default and less likely to cure, based on the coefficient table. Based on the Board's experience and expertise, these coefficient findings are likely due to the fact that borrowers with larger loans tend to have larger payments, making them more likely to default. The log specification is used commonly in statistical models. Using the log of loan size is approximately equivalent to assuming that constant percentage changes in loan size will have constant effects (i.e. a 3 percent increase in loan size will always impact the model similarly).
- Investment indicator: Loans secured by investment properties are riskier and are less likely to cure, as demonstrated by the negative coefficient on this variable.
- Origination spread: As described in earlier equations, higher origination spread reflects additional risk. Loans with higher origination spread are less likely to cure, as evidenced by the negative coefficient on this variable.
- Updated LTV: Consistent with the explanation in earlier equations, borrowers with less equity in their properties are less likely to cure. This is further evidenced by the negative coefficient on this variable.

FRM, Delinquent-to-Payoff

- Change in HPI over previous year: Similar to in the current-to-payoff equation, the coefficient on this variable indicates that rising house prices are associated with increased payoffs from delinquent, likely because the increase in house prices increases the likelihood that the borrower can pay off the entire loan balance.
- Loan size (log): Borrowers with larger loan amounts tend to be more likely to default and less likely to pay off. As demonstrated by the negative coefficient on this variable, borrowers with larger loans are less likely to pay off. This is consistent with the theory that borrowers with large loans tend to have more difficulty liquidating their properties. The log specification is used commonly in statistical models. Using the log of loan size is approximately equivalent to assuming that constant percentage changes in loan size will have constant effects (i.e. a 3 percent increase in loan size will always impact the model similarly).
- Investment indicator: Loans secured by investment properties are riskier and are less likely to pay off, as demonstrated by the negative coefficient on this variable.
- Updated LTV: Borrowers with less equity in their properties are less likely to pay off. This is further evidenced by the negative coefficient on this variable.

FRM, Delinquent-to-Delinquent

- Judicial foreclosure state indicator: Loans from judicial states are more likely to default and less likely to stay delinquent, as pointed out in Cordell and Lambie-Hanson (2016) and further evidenced by the negative coefficient on this variable. As previously noted, when using the model to project loss rates, a single value of this variable is applied to all loans, based on the share of industry balance reported in the FR Y-14M that is secured by property in a judicial state. This avoids penalizing loans based on their location.
- Industry COVID-19 forbearance rate: This is defined as in "FRM, Current-to-Delinquent." During the COVID-19 pandemic period, forbearance programs and other government support programs reduced the cost of nonpayment to borrowers, increasing default rates observed in the First Lien PD Data (and thus reducing the likelihood of remaining delinquent) during this period.[177]
- Change in HPI over previous year: Rising house prices make it more likely borrowers will not proceed to default, as observed based on the positive coefficient on this variable.
- Origination credit score: As described in "FRM, Delinquent-to-Current," and evidenced by the negative coefficient on this variable, borrowers with higher credit scores are more likely to proceed to default once they reach delinquency. While lower credit score borrowers are more likely to fall in and out of delinquency, higher credit scores are associated with proceeding to default. Note that the model assigns a value of "0" in the credit score field when it is missing and applies a flag to identify loans with missing credit scores to separately assess the risk of loans missing credit scores. When using the model to project default rates, the Board does not apply this variable; instead, the Board imputes the industry 10th percentile credit score as described in Section C.ii.a.(3).
- Loan size (log): Borrowers with larger loan amounts tend to be more likely to default, based on the coefficients in this equation. Based on the Board's experience and expertise, this coefficient is likely due to the fact that borrowers with larger loans tend to have larger payments, making them more likely to default. The log specification is used commonly in statistical models. Using the log of loan size is approximately equivalent to assuming that constant percentage changes in loan size will have constant effects (i.e. a 3 percent increase in loan size will always impact the model similarly).
- Investment indicator: Loans secured by investment properties are riskier and are more likely to default, based on the negative coefficient on this variable.
- Secondary residence flag: Loans secured by second homes are riskier and are more likely to default, based on the negative coefficient on this variable.
- Origination spread: Riskier loans as measured by their origination spread are more likely to default, based on the negative coefficient on this variable.

ARM, Current-to-Delinquent

- Origination credit score (knots at 660 and 720): As credit score increases, the likelihood of delinquency falls, as observed in Krainer and Laderman (2011). Board analysis of First Lien PD Data shows that this effect is non-linear; risks of becoming delinquent

[177] The Board's definition of delinquency relies on the time elapsed between the payment due date and the current time period, regardless of forbearance status. Therefore, the model assesses loans in forbearance as delinquent or in default if sufficient payments are missed, regardless of forbearance status.

decrease faster for higher credit scores, especially those above 720, as demonstrated by the negative coefficients on these two knots. Note that the model assigns a value of "0" in the credit score field when it is missing and applies a flag to identify loans with missing credit scores to separately assess the risk of loans missing credit scores. When using the model to project default rates, the Board does not apply this variable; instead, the Board imputes the industry 10th percentile credit score as described in Section C.ii.a.(3).

- Industry COVID-19 forbearance rate: As defined in "FRM, Current-to-Delinquent." During the COVID-19 pandemic period, forbearance programs and other government support programs reduced the cost of nonpayment to borrowers, increasing delinquency rates observed in the First Lien PD Data during this period.[178]
- GSE repurchase flag: As defined in "FRM, Current-to-Delinquent." Since repurchases are generally made due to underwriting defects, these loans are riskier and more likely to go delinquent, as observed based on the positive coefficient on this variable. GSE repurchases are discussed in further detail in Section C.ii.a.(3).
- Change in unemployment rate over previous year: Academic literature, such as Elul et al. (2010), demonstrate the importance of "double trigger" in predicting mortgage delinquency. The double trigger refers to the joint shocks to home equity (driven by falling home prices) and liquidity (driven by income loss); both factors are often needed to cause default. The change in unemployment rate proxies for the liquidity shock. While the model does not observe individual income levels, increases to state-level unemployment rate are predictive of income loss among borrowers in that state. Increases in unemployment rate are associated with increased delinquency, as observed in the coefficient.
- Change in HPI over previous year: House price index is a measure of the level of house prices. Increases in HPI reflect appreciation, while decreases in HPI reflect house price decline.[179] House price changes are the other portion of the double trigger described in the previous bullet. House prices enter the equation both directly in this term as well as via the updated LTV calculation. Empirically, as shown in the coefficient on this variable, year-over-year changes are predictive of delinquency.
- Interest only indicator: This term identifies loans where the borrower is required to only make interest payments (as opposed to interest and principal payments) at origination. Borrowers with interest only loans are riskier than borrowers with amortizing loans as observed historically in the First Lien PD Data during the 2008 financial crisis, as evidenced by the positive coefficient on this variable.
- Loan age (knots at 12 and 24 months): The loan age terms capture the increasing delinquency risk of the loan due to seasoning (meaning the amount of time a borrower has held a loan), increasing at a decreasing rate over time. After 24 months, the effect of additional aging is close to zero, as shown in the coefficients on the loan age variables.

[178] The Board's definition of delinquency relies on the time elapsed between the payment due date and the current time period, regardless of forbearance status. Therefore, the model assesses loans in forbearance as delinquent or in default if sufficient payments are missed, regardless of forbearance status.

[179] *See* Section C.ii.a.(3) for details on the assignment of house price index to each loan.

- Origination year (2005, 2006, 2007,[180] 2009, 2010, 2011, and 2012 and later): These variables capture underwriting changes that are not captured by the observable variables. The 2005-2007 vintages are the “bubble vintages” and have higher delinquency rates than the 2003-2004 base vintages, whereas 2009-2011 and 2012+ vintages are post-crisis vintages under tighter underwriting standards and thus are less likely to become delinquent than the 2002-2003 base vintages. These coefficients reflect the estimated parameters based on historical data. When using the model to project PD, however, the model treats loans originated in or after 2009 as having the risk level of loans originated prior to 2005; essentially, less risky than the “bubble vintages” but riskier than the coefficients on the post-crisis coefficients would indicate. This assumption is aligned with the stress testing principle of conservatism, due to uncertainty in the true risk level of recent originations. While some risk factors, such as underwriting quality, have improved since the period before the financial crisis, other risk factors, such as the propensity to engage in fraud[181] or borrowers de-prioritizing mortgage payments compared to their other liabilities,[182] could likely return during another downturn in the housing market. Furthermore, some of those changes in borrower behavior (such as payment prioritization) are based on future expectations in housing price movements, and cannot be effectively accounted for using contemporaneous housing prices. Given that recent vintages have not been exposed to a housing downturn, the Board believes that these coefficients may be imprecisely estimated, further motivating a conservative approach. One marker that indicates that recent vintages may be riskier than anticipated is that debt-to-income ratios have increased from their lows in the early 2010s, based on Board review of historical FR Y-14M data.
- Retail indicator: Loans that were originated through retail channels are less risky since the seller/servicer controls the underwriting, as evidenced by the negative coefficient on this variable.
- Origination spread (knot at 3 percent): As with FRMs, the origination spread for ARMs is calculated as the difference between the origination interest rate and the 10-year Treasury yield at origination. A higher spread at origination indicates that the lender required a higher interest rate to cover otherwise unobserved risk. While the origination spread is

[180] Because 2008 vintages have similar delinquency rates than 2003-2004 vintages, the model treats 2008, as well as 2003 and 2004, as “base vintages.” Around 2008, ARM originations fell sharply as a result of the ongoing housing market contraction. For instance, ARM originations fell from 34 percent of new originations in 2006 to 6 percent in 2008. See Moench, Vickery, and Aragon (2010). The contraction in ARM originations likely add volatility to the characteristics of the ARMs that were originated, making the estimation of a unique coefficient challenging. In practice, the observed similar delinquency rates are likely the result of changes in the market; as the riskier-than-baseline loans of 2005-2007 shifted to the less-risky-than-baseline loans of 2009 and after, loans originated in 2008 ultimately had similar riskiness to the 2003-2004 loans that are used in the model as the baseline. Therefore, there is no coefficient assigned to 2003, 2004, or 2008 vintages in this equation. Moench, E., J. Vickery, and D. Aragon (2010). Why is the Market Share of Adjustable-Rate Mortgages So Low. Federal Reserve Bank of New York Current Issues in Economics and Finance 16(8).

[181] Occupancy fraud was widespread during the great financial crisis period and remains a potential risk in recent periods, as documented by Elul, Payne, and Tilson (2023). Elul, R., A. Payne, and S. Tilson, 2023, “Owner-Occupancy Fraud and Mortgage Performance,” Real Estate Economics 51(5): 1137-1177.

[182] There is historical evidence that borrowers deprioritize mortgage payments during a housing downturn. See Conway, J., N. Fischl-Lanzoni, and M. Plosser. “When the Household Pie Shrinks, Who Gets Their Slice?” Federal Reserve Bank of New York, (6 March 2025), https://libertystreeteconomics.newyorkfed.org/2025/03/when-the-household-pie-shrinks-who-gets-their-slice.

predictive of delinquency for the bulk of loans, extreme cases are idiosyncratic, and therefore the model uses a spline knot at 3 percent to reflect that marginal impacts are lower at the extremes.

- Updated LTV: As defined in “FRM, Current-to-Delinquent.” Updated LTV is grouped into buckets to reflect changing impacts of LTV on non-payment risk at different points in the distribution. The following buckets are used in the model: [0,50), [50,60), [60,70), [70,80), [80,90), [90,100), [100,110), [110,130) and [130, 150); coefficients reflect risk compared to that of a loan with LTV greater than 150. The large number of buckets were chosen to granularly assess the impact of changes in updated LTV on the likelihood of becoming delinquent; the Board determined that a larger number of buckets risked creating spurious coefficients, while a smaller number of buckets risked failing to account for true differences in non-payment risk across loans. In general, the coefficients show that loans with lower updated LTV have lower risk of transitioning to delinquency. For discussion of the impacts of not considering amortization in this calculation, see Section C.ii.a.(4).
- Fixed rate window (indicator for 2–3-year initial rate period): ARMs tend to have initial periods of varying lengths during which the interest rate is fixed before the rate begins to float. Academic literature, such as Elul (2009), shows that shorter initial rate periods were historically offered to weaker borrowers; this variable proxies for the effect of these products being offered to weaker borrowers. This is evidenced by the positive coefficient on this variable.
- After fixed rate period indicator: Loans become riskier after their initial reset, as observed in the literature (see Pennington-Cross and Ho, 2010)[183] demonstrated by the positive coefficient on this variable. This is likely due to borrowers with ARMs that have reset being a selection of borrowers whose credit worthiness did not allow them to refinance earlier.
- Interest only after fixed rate period indicator: The increased risk of transitioning to delinquency is empirically stronger for loans that are interest only at origination, as evidenced by the positive coefficient on this variable.
- Rate change and initial rate reset interaction: This is defined as the change in the 3-month Treasury rate since origination, applied only to ARMs that have hit their initial rate reset. For ARMs that have hit their first reset, increased interest rates lead to increased risk of transitioning to delinquency, as evidenced by the positive coefficient on this variable. This is due to the fact that increased interest rates are associated with higher-than-expected payments for these borrowers.
- Teaser after fixed rate period indicator: “Teaser rates” refer to a practice where the lender offers a low initial interest rate that increases after the end of the initial fixed rate period. In the model, it is assumed that rates are teaser rates when the spread over the 3-month Treasury rate is less than 0.5 percent for ARMs with a less than 3-year initial term, or when the spread over the 10-year Treasury rate is less than 0.5 percent for ARMs with more than a 3-year initial term. Rates this low are unusual outside of the context of teaser rates. ARMs with teasers are more likely to go delinquent after the initial rate reset, as

[183] Pennington-Cross, A. and Ho, G. (2010), The Termination of Subprime Hybrid and Fixed-Rate Mortgages. Real Estate Economics, 38: 399-426.

the increased payments after the end of the teaser rate create a payment shock that strains borrower finances. This is supported by the positive coefficient on this variable.

- Teaser after 2010 indicator: Teaser rate loans originated in 2011+ are riskier than earlier vintages, as evidenced by the positive coefficient on this variable.
- Origination spread of teaser: Because teaser rates are temporary, the spread of the (teaser) origination interest rate over the 10-year yield is generally not as predictive of nonpayment risk as origination spread is for loans that do not have teaser rates. This term takes this factor into account. This is evidenced by the coefficient on this variable, which is negative, but lower in magnitude than the positive coefficient on spread at origination (for all loans) in the same table. The combined impact of these two terms is that the model is substantially less sensitive to the spread at origination for loans with teaser rates than it is for other loans.

ARM, Current-to-Payoff

- Origination credit score (spline at 720): There is a weak, positive relationship in the historical First Lien PD Data between credit score and refinance frequency, as observed by the positive coefficient on this variable in Table C3. Borrowers with higher credit scores are more likely to get approved for a refinance. The model also includes a dummy for missing credit score at origination. Note that the model assigns a value of “0” in the credit score field when it is missing and applies a flag to identify loans with missing credit scores to separately assess the risk of loans missing credit scores. When using the model to project default rates, the Board does not apply this variable; instead, the Board imputes the industry 10^{th} percentile credit score as described in Section C.ii.a.(3).
- GSE repurchase flag: As defined in “FRM, Current-to-Delinquent.” Generally, loans repurchased from GSEs are more likely to pay off than other loans, based on the positive coefficient on this variable.
- Change in HPI over previous year: Borrowers tend to be more likely to pay off their loans in appreciating housing markets, as observed by the positive coefficient on this variable.
- Interest only indicator: Borrowers with interest only loans historically were lower quality than borrowers with amortizing loans and thus less able to refinance, as evidenced by the negative coefficient on this variable.
- Loan age (knot at 12 months): Analysis of First Lien PD Data shows that payoff rates increase rapidly for the first twelve months after origination; however, after that, the relationship flattens out.
- Updated LTV: As defined in “FRM, Current-to-Delinquent.” Updated LTV is grouped into buckets to reflect changing impacts of LTV on non-payment risk at different points in the distribution. In general, loans with lower updated LTV are more likely to prepay, particularly for loans with a mark-to-market LTV less than 80 percent (based on the coefficient estimates on these variables). This is consistent with the expectation that borrowers need a sizable equity cushion to fully exercise most prepayment options, but beyond that there is only minimal impact of increasing equity. The following buckets are used in the model: [0,50), [50,60), [60,70), [70,80), [80,90), [90,100), [100,110), and [110,130). The large number of buckets were chosen to granularly assess the impact of changes in updated LTV on the likelihood of payoff; the Board determined that a larger

number of buckets risked creating spurious coefficients, while a smaller number of buckets risked failing to account for true differences in payoff likelihood across loans. Each of the coefficients compares the likelihood of payoff compared to an equivalent loan with updated LTV above 150.

- Burnout: As defined in "FRM, Current-to-Payoff." For ARMs, this variable is less impactful than for FRM based on the observed coefficient, possibly because the incentive to refinance an ARM is less related to shifts in interest rates and more closely tied to the date of rate reset compared to an FRM.
- Seasonality indicator (Q1 and Q2): As demonstrated by the coefficients on these variables, higher payoff rates are observed in the first two quarters of the year. This is consistent with traditional patterns of seasonality in mortgage prepayment; see the "FRM, Current-to-Payoff" section for more discussion of the impact of seasonality.
- Loan size (log) (floored at $60,000): In the historical First Lien PD Data, for loan sizes below $60,000, there is minimal impact of loan size on payoff; above this value, payoff increases with loan size as the refinance incentives and ability to pay off the loan change with loan size; this is evidenced by the positive coefficient on the knot at $60,000. The log specification is used commonly in statistical models. Using the log of loan size is approximately equivalent to assuming that constant percentage changes in loan size will have constant effects (i.e. a 3 percent increase in loan size will always impact the model similarly).
- Investment indicator: Loans secured by investment properties are less likely to be refinanced, as evidenced by the negative coefficient on this variable.
- Secondary residence flag: Loans secured by second homes are less likely to be refinanced, as evidenced by the negative coefficient on this variable.
- Fixed rate window (indicators for 0-6 month, 1 year, and 2–3-year initial rate period): ARMs with shorter initial rate periods have higher payoff rates than longer term (5 or 7-year initial rate period) ARMs, as evidenced by the positive coefficients on these variables.
- After fixed rate period indicator: Loans that have passed their initial reset date without paying off the loan are less likely to prepay in the future, as evidenced by the negative coefficient on this variable, subject to the caveats in the next bullet.
- Time to initial rate reset (end of fixed rate period) (indicators for < 12 months prior to initial reset, < 6 months prior to initial reset, < 6 months after initial reset, and < 12 months after initial reset): Conversely to the above description that loans that passed their initial reset date without paying off are less likely to do so going forward, loans are significantly more likely to pay off immediately before or immediately after the first rate reset, as observed in Pennington-Cross and Ho (2010) and confirmed by the coefficients on these variables. The above paper builds on other literature and theory that suggests ARM borrowers commonly refinance around the first reset date.
- Rate change and initial rate reset interactions (interaction with <12 months to initial rate reset, <6 months to initial rate reset, <6 months after initial rate reset, <12 months after initial rate reset, and 0-6 month initial fixed rate window): As described previously, the "rate change" contemplated in this term is the difference between the 3-month Treasury rate at origination compared to the 3-month Treasury rate in the current period. In cases where this interest rate has increased from origination, borrowers face increased payments, incentivizing refinance. This is notably impactful immediately before or after

the first interest rate reset, as well as for ARMs without an initial fixed rate period, based on the coefficients.

- Teaser after fixed rate period indicator: The coefficient on this variable suggests that ARMs with teaser rates are more likely to prepay after the initial reset, due to the increased payment that usually is associated with the end of the teaser rate.
- Origination spread over FRM rate (knot at 1 percent): This is defined as the difference between the origination interest rate and the average 30-year fixed-rate mortgage rate at origination. Larger spreads relate to riskier borrowers who may have harder times refinancing, and thus payoff at lower rates, as evidenced by the negative coefficient on this variable. Spreads below 1 percent are rare and may reflect idiosyncratic factors, so this variable only accounts for differences due to spreads above 1 percent.
- Current spread over FRM rate (knot at 2.5 percent): This is defined as the difference between the current (not origination) interest rate and the average 30-year fixed-rate mortgage rate in a given period. When this spread is higher, borrowers can often refinance their loan into a lower interest rate fixed-rate mortgage. As a result, higher spreads are associated with increased chance of payoff, but that incentive decreases for spreads over 2.5 percent. Very wide spreads are likely indicative of other risks. These trends are observable in the equation coefficients.

ARM, Delinquent-to-Current

- Judicial foreclosure state indicator: As pointed out in Cordell and Lambie-Hanson (2016) and further evidenced by the negative coefficient on this variable, borrowers in long timeline judicial states are more likely to stay persistently delinquent and less likely to cure. As previously noted, when using the model to project loss rates, a single value of this variable is applied to all loans, based on the share of industry balance reported in the FR Y-14M that is secured by property in a judicial state. This avoids penalizing loans based on their location.
- Change in HPI over past year: Rising house prices increase the likelihood of curing, as observed based on the positive coefficient on this variable.
- Origination credit score: As described in the review of literature above, the model coefficients show that, consistent with studies such as Adelino et al. (2013) and ITDC (2023-2024), loans with higher origination credit scores are more likely to default and less likely to cure. While higher credit borrowers are less likely to go initially delinquent, when they do it is generally for some sustained shock, like unemployment or loss of income, making them less likely to cure. Note that the model assigns a value of “0” in the credit score field when it is missing and applies a flag to identify loans with missing credit scores to separately assess the risk of loans missing credit scores. When using the model to project default rates, the Board does not apply this variable; instead, the Board imputes the industry 10th percentile credit score as described in Section C.ii.a.(3).
- Investment indicator: Loans secured by investment properties are riskier and are less likely to cure, as demonstrated by the negative coefficient on this variable.
- Origination spread: As described in earlier equations, higher origination spread reflects additional risk. Loans with higher origination spread are less likely to cure, as evidenced by the negative coefficient on this variable.

- Updated LTV: Consistent with the explanation in earlier equations, borrowers with less equity in their properties are less likely to cure. This is further evidenced by the negative coefficient on this variable.

ARM, Delinquent-to-Payoff

- Change in HPI over previous year: Similar to this term in the current-to-payoff equation, the coefficient indicates that rising house prices are associated with increased payoffs from delinquent, likely because the increase in house prices increases the likelihood that the borrower can pay off the entire loan balance.
- Investment indicator: Loans secured by investment properties are riskier and are less likely to pay off, as demonstrated by the negative coefficient on this variable.
- Origination spread: Riskier loans as measured by their origination spreads are less likely to pay off, as demonstrated by the negative coefficient on this variable.
- Updated LTV (flag for >=90 percent): Loans with extremely low or negative equity are less likely to be able to pay off their loan in full. This theoretical statement is evidenced by the negative coefficient on this variable. Unlike in the FRM delinquent-to-payoff equation, the Board assessed based on the historical First Lien PD Data during the period used to estimate the model coefficients that the impact of updated LTV on payoff for delinquent ARMs is concentrated around an updated LTV at 90 percent, rather than smoothly decreasing as updated LTV increases. As a result, this variable is defined as a flag for whether or not updated LTV is above 90 percent.

ARM, Delinquent-to-Delinquent

- Judicial foreclosure state indicator: Loans from judicial states are more likely to default and less likely to stay delinquent, as pointed out in Cordell and Lambie-Hanson (2016) and further evidenced by the negative coefficient on this variable. As previously noted, when using the model to project loss rates, a single value of this variable is applied to all loans, based on the share of industry balance reported in the FR Y-14M that is secured by property in a judicial state. This avoids penalizing loans based on their location.
- Industry COVID-19 forbearance rate: As defined in "FRM, Current-to-Delinquent." During the COVID-19 pandemic period, forbearance programs and other government support programs reduced the cost of nonpayment to borrowers, increasing default rates observed in the First Lien PD Data (and thus reducing the likelihood of remaining delinquent) during this period.[184]
- Change in HPI over previous year: Rising house prices make it more likely borrowers will not proceed to default, as observed based on the positive coefficient on this variable.

[184] The Board's definition of delinquency relies on the time elapsed between the payment due date and the current time period, regardless of forbearance status. Therefore, the model assesses loans in forbearance as delinquent or in default if sufficient payments are missed, regardless of forbearance status.

- Origination credit score: As described in "ARM, Delinquent-to-Current," and evidenced by the negative coefficient on this variable, borrowers with higher credit scores are more likely to proceed to default once they reach delinquency. While lower credit score borrowers are more likely to fall in and out of delinquency, higher credit scores are associated with proceeding to default. Note that the model assigns a value of "0" in the credit score field when it is missing and applies a flag to identify loans with missing credit scores to separately assess the risk of loans missing credit scores. When using the model to project default rates, the Board does not apply this variable; instead, the Board imputes the industry 10^{th} percentile credit score as described in Section C.ii.a.(3).
- Investment indicator: Loans secured by investment properties are riskier and are more likely to default, based on the negative coefficient on this variable.

(3) Adjustments and Data Cleaning Steps

Estimation Sampling and Loan Inclusion

This section describes the sampling and filtering processes used to apply the First Lien PD Data to produce the First Lien PD Model parameters.

First, the dataset is filtered to a 10 percent sample. Random sampling is used to ensure the data remain representative of the entire First Lien PD Data while ensuring the size of the dataset is manageable for modeling; including more loans increases the run time and memory cost of implementing the model without substantially increasing the reliability of the results.

From this sample, loans originated between January 2002 and December 2021 are retained, along with performance data on these loans through September 2022. Due to data quality concerns for ARMs reported prior to the end of 2003, only ARMs originated between December 31, 2003 and December 2021 are retained. The First Lien PD Data is particularly useful in the supervisory stress test because it provides coverage over a long history, including during the 2008 financial crisis—during which there was significant stress to the housing market. While data prior to 2002 are available in the data, the quality of the data are weaker for earlier years. In particular, a large share of loans prior to 2002 are missing credit score at origination, a key predictor of mortgage default. Given changes in the mortgage market over time, using data prior to 2002 may lead to estimates that are not representative of the current mortgage portfolio. The start date of January 2002 is chosen for FRMs and the end of 2003 is chosen for ARMs to balance the goals of including data covering a wider variety of time periods and macroeconomic environments in the model estimation sample—which expands the range of business environments the model is suited to assess—with ensuring sufficient data quality; the Board uses a later start date for ARMs due to concerns about ARM data quality prior to 2003 in the First Lien PD Data. Using data through September 2022 ensures coverage of the model across an entire business cycle and through recent periods, including the COVID-19 pandemic period. The Board regularly monitors model performance to observe whether the model continues to perform effectively, including by applying the model parameters to historical loan and macroeconomic data and comparing projected default rates to actual default rates. This monitoring shows that, as of the time of publication, the model continues to perform well when applied to recent data.

Given this starting dataset, additional filters are applied to ensure the data are representative and of sufficient quality for inclusion in the model.[185] First, loans are included only if the entire loan history is available. Loans that are missing observations at the beginning of their history are problematic because they are susceptible to survivorship bias,[186] which can bias the model estimates. In practice, to minimize the impact of survivorship bias, regardless of the origination date of the loan, loans are only included if they are first observed within six months of origination (for FRMs) or twelve months of origination (for ARMs). The less restrictive filter for ARMs is reflective of the larger share of ARMs that are not available until

[185] Note that ARM and FRM are modeled separately, but are subject to similar data cleaning processes, outlined in this section.

[186] To understand survivorship bias, consider two loans, each of which is not reported for the first 6 months after origination. The first loan defaults in the first 6 months, while the second loan remains current during this period. Because the first loan has defaulted already, it will never be reported, while the second loan will begin to be reported after the 6 months have elapsed. Including the second loan in the estimation data would introduce bias, as loans missing observations are only included if they do not transition to default or payoff prior to appearing in the data.

many months after origination; the twelve-month cut-off balances concerns about survival bias with ensuring a large and representative sample.

Certain additional filters are applied to ensure representativeness. In particular, only mortgages that were originated for the purpose of home purchase or refinance (as opposed to other purposes, such as home improvement) are included in the sample. Loans originated for the purpose of home purchase or refinance account for over 95 percent of portfolio loans reported on the FR Y-14M as of December 2024. Additionally, loans that are insured or guaranteed by the U.S. government (such as FHA or VA loans) are not included as they are assumed to have minimal financial risk to the firm in the case of default, even if they are held on firm balance sheets.[187]

Importantly, only portfolio loans are included in the sample. Portfolio loans are loans held on a firm's balance sheet; this is in contrast to loans that are originated and sold to third parties.[188] Portfolio loans have different features and different incentives compared to other loans; the Board calibrates the model parameters based only on portfolio loans for representativeness. One nuance is that loans are not fixed as portfolio or non-portfolio loans throughout their history; they may remain on the originator's balance sheet for months prior to being sold or be returned or repurchased (sometimes referred to as "put back") to the originator's balance sheet in certain cases. To ensure consistent treatment of loans in these cases, the model treats loans as portfolio loans only when the final observation of a loan is held on the firm's

[187] The supervisory stress test model assumes firms do not incur losses on loans insured by government programs, due to the large share of the balance that is insured.
[188] In addition to portfolio loans, institutions also often service loans that are not on its balance sheet, most often when the loan is securitized, as described in Section C.i.a. Loans that are serviced by an institution but not on the institution's balance sheet are neither included in the data used to calibrate the PD model parameters, nor included in the data used to project first lien losses in the supervisory stress test.

balance sheet;[189] other loans are removed from the sample. Furthermore, loans designated as Ginnie Mae loans are removed from the sample even if they are last observed as a portfolio loan; these loans are government guaranteed, even though they are technically returned to firm balance sheets when they reach 90 or more days past due.[190]

Next, certain loans are removed due to signs of unusual or outlier data to avoid such data creating an adverse impact on model performance and results. In general, criteria are less stringent for ARMs, reflecting the smaller number of ARMs in the data and increased prevalence of unusual data trends. Loans with any of the following characteristics are removed:

- FRMs for which the balance increases by more than 5 percent month-over-month, despite remaining current; or ARMs for which this occurs on at least two separate observations. This filter and the filter in the below bullet ensure outlier data are removed without unnecessarily removing loans. These filters capture a very small percentage of loans (less than 0.5 percent).
- FRMs for which the balance increases by more than the calculated interest in a given month in at least two separate observations while remaining current; or ARMs for which this occurs on at least four separate observations.[191]
- Loans that are current for which the observed balance is more than $1,000 above the origination balance amount, unless a balance increase is observed during a period where the loan transitioned from seriously delinquent to current. While balance can increase above origination amount when a loan converts from seriously delinquent to current due to loan modification, it is unusual otherwise.
- Loans with outlier values of origination loan-to-value ratio (below 0 percent or greater than 125 percent).
- FRMs for which the interest rate changes by more than 0.5 percent, unless the loan is marked as having been modified. Since FRMs are fixed rate products, the interest rate should generally be constant.
- Loans with a gap of more than 120 days between observations, as these reflect loans with multiple-quarter gaps during which performance is not observed.
- Loans that are only observed in a single period before leaving the dataset, often because they are transferred or sold. The single observation provides insufficient information to track the loan's probability of default over time.

[189] Formally, loans are also included if it is unknown if the final observation is a portfolio loan, but the loan was previously a portfolio loan and not in a security.
[190] As described in Section C.i.a, losses on non-portfolio mortgage loans, such as mortgage-backed securities, are accounted for via the Securities Model. *See* the Section A.ii in the Market Risk Models Documentation (Securities Model).
[191] ARMs are also removed if the balance increases by more than 5 percent on one occasion and by more than the interest amount on two other occasions while remaining current.

- Loans for which the product type is not consistent with its classification as an FRM or ARM.

Additionally, loans are excluded if they are missing variables used in the model. This includes loans with missing property state, or for which the property is not located in the 50 U.S. states or Washington, DC. Because house price index and unemployment rate are applied at the state- (or county-) level, a value cannot be applied for loans outside of these geographies. Furthermore, in most cases, domestic first lien balances exclude loans to borrowers in U.S. territories (see FR Y-9C instructions at 391, glossary entry for “Domestic Office”); as a result, these loans are not in the scope of loans covered by the First Lien Model, which covers domestic exposures only.

An exception to the general exclusion of loans missing variables in the model is for origination credit score, which is important for modeling but is missing in a sizable share of observations. The process for including loans with missing origination credit score is detailed in “Estimation Data Cleaning and Preparation.”

Among ARMs, certain filters are applied in addition to the above. While these filters are not necessarily removing erroneous data, the filtered loans are sufficiently unusual, and their characteristics are sufficiently different from other loans that the Board determined it was appropriate to exclude these loans in the population used to estimate the model—in line with the stress testing principle of simplicity—to avoid the additional complexity from modeling these unusual loans:

- Option ARM loans, which were relatively common prior to the 2008 financial crisis but became very rare in recent years. As the characteristics of these loans differ significantly from other ARMs, they are removed.
- Loans for which the period of time for which the interest rate is fixed prior to the first reset is missing or greater than 10 years. The missing observations are possibly

erroneous, while the loans with fixed periods of greater than 10 years are unusual and may behave differently than other ARMs with shorter fixed-rate periods.

Lastly, loans are generally included only until they first default, regardless of future cures. A small number of exceptions are made to account for rare situations where it is inappropriate to remove the additional loan history:

- The loan is in default status for only a single observation (month). This suggests a transient default.
- The loan was in default status during the pandemic period, defined as between April 2020 and December 2021. Due to forbearance programs offered during this time, many borrowers were missing payments in accordance with their forbearance terms and were not treated by the lenders as in default. To account for potential differences in behavior among loans exiting forbearance from other loans, loans that exited forbearance and returned to current status are retained in the sample.

Even though these filters remove a material portion of the original observations, especially for ARMs, the number of observations remain sufficient for producing stable, reasonable coefficients in the final model, as demonstrated by the high level of precision in the estimates of the key model coefficients that demonstrate precise and statistically significant results. Since the large share of observations removed from the data could raise concerns about representativeness, the Board compared key variables in the final dataset to equivalent fields in the FR Y-14M report used to project losses to ensure that the large number of filtered loans does not impact the reliability of the model. Among overlapping periods, the FR Y-14M data aligns well with the First Lien PD Data on key indicators such as origination credit score and origination LTV. Given these comparisons, the filtered data used to estimate the model parameters appear to reasonably approximate the data used to project losses.

Estimation Data Cleaning and Preparation

Loans that remain in the data following the filtering process described above are cleaned to prepare for inclusion in the model. Notably, while data are reported at monthly frequency, the model relies on quarterly transitions, so the monthly observations must be aggregated into quarterly data. For most dynamic variables, this is implemented by using the value reported in the last month of a quarter. Using the quarter-end observation aligns with the macroeconomic variables applied in the model and provide a consistent definition across time. The exception to this implementation is payment status (current, late, payoff, or default). For this variable, loans are considered defaulted if a default occurs at any point in a quarter; payoff if paid off at any point in the quarter (as long as the payoff was not a short sale or other event that would trigger a default condition); servicing transfer if marked as such at any point during the quarter;[192] delinquent if observed at any point in the quarter as long as payoff, default, or servicing transfer was not separately observed; and, finally, current if none of the other statuses are observed during the quarter. This is in line with the stress testing principle of conservatism, as it ensures that delinquencies and defaults, respectively, are accounted for even if the conditions are only triggered at intermediate point during the quarter.

Additionally, in the First Lien PD Data, origination credit score is missing noticeably often, but disproportionately in earlier vintages. To avoid biasing the sample towards later vintages and further reducing the sample size, origination credit score is set to zero for these loans and an indicator variable for missing values is included in all equations where origination credit score is used.

Next, macroeconomic data is merged with the cleaned First Lien PD Data sample. The macroeconomic data is applied in the model both as of the origination date of the loan (for instance, to calculate spread at origination) as well as contemporaneously (for instance, to calculate the percent change in HPI). Macroeconomic data is included as described below:

[192] As previously stated, the First Lien Model does not model the probability of servicing transfers.

- House price index, sourced from a third-party vendor.[193]
- Unemployment rate,[194] produced by the Bureau of Labor Statistics.
- U.S. mortgage rate, obtained from the Primary Mortgage Market Survey of the Federal Home Loan Mortgage Corporation. The mortgage rate is defined as the quarterly average of the weekly series for the interest rate of a conventional, conforming, 30-year fixed-rate mortgage.
- Various maturities of yields of U.S. Treasuries, sourced from the Federal Reserve Board of Governors (see "Selected Interest Rates, H.15 Release").

Origination data (house price index at origination, as well as interest rate variables as of origination) are merged in at a monthly frequency, while contemporaneous data are merged at a quarterly frequency, corresponding to the last month of a quarter. For contemporaneous data, the model's use of quarterly transitions necessitates these frequencies and aligns with the frequency used in projections. For origination data, the monthly data provide additional precision in circumstances where macroeconomic variables moved substantially over the course of a quarter.

For macroeconomic variables that are merged at the national level (in particular, measures of interest rates), the Board assigns the same macroeconomic variable value to all loans in a given quarter. Unemployment rate is merged at the state level, based on the state in which the property is located. House price index is merged at the county level when possible, based on a mapping of the reported ZIP code of the property to a county. For ZIP codes that cannot be mapped to a county, or for counties for which house price index is not provided,[195] the state-level house price index is used instead. This process allows for the inclusion of house price information at the county level when available to ensure the model is reflective of true housing market conditions.

[193] The Board does not adjust the values of the house price index sourced from the vendor when estimating the model coefficients (such as by seasonally adjusting the data).
[194] The First Lien PD Model is estimated using the seasonally adjusted unemployment rate as of the end of a given quarter.
[195] House price index is not reported for all counties. Generally, smaller counties with fewer housing transactions are less likely to have house price index available.

In addition to macroeconomic variables, the historical share of portfolio loans at large banks, as defined by the data vendor, in forbearance related to COVID-19 is included starting in April 2020 to account for the impacts of the COVID-19 pandemic and the response to the pandemic on the mortgage market. This share is sourced from a third-party vendor. This share is calculated nationally, and the same value is assigned to all loans in a given period. For periods prior to April 2020, a value of zero is assigned in this field.

Finally, conforming loan limits are assigned to identify "jumbo" mortgages. The maximum values of conforming loans are assigned using historical data available from Fannie Mae.[196] These values are assigned to loans based on the origination year and the number of units of the property. For simplicity and consistency across different geographies, the model does not account for the variation in conforming loan limits across different geographies.[197] While this limits the ability of the model to account for variation based on different conforming loan limits in different geographies, it reduces model complexity and ensures that loans are not treated differently based on property location. Additionally, conforming loan limits apply based on the date the loan is delivered to a GSE, rather than the date the loan is originated. Nevertheless, most loans are delivered to a GSE shortly after origination; therefore, the impact of any delay on the eligibility of a loan to be delivered to a GSE is small.

[196] *See* "Originating & Underwriting Loan Limits," Fannie Mae, https://singlefamily.fanniemae.com/originating-underwriting/loan-limits.

[197] Loans secured by properties in Alaska, Guam, Hawaii, and the U.S. Virgin Islands have higher conforming loan limits, and loans secured by properties in other geographies that are "high-cost areas" can have higher conforming loan limits as well.

Projection Data Cleaning and Preparation

The model parameters estimated from the model are applied to the reported firm data on the FR Y-14M to produce projections of PD and payoff rates. Similar to the estimation data, several data cleaning steps are necessary to prepare the projection data to be used.

First, the following data reported on the FR Y-14M that are not appropriate for use in model projections are removed:

- Loans held for investment under a fair value option (FVO) or held for sale (HFS) are removed, as losses for these loans in the supervisory stress test are projected by the FVO Model.
- Loans that are marked as having a commercial purpose are removed. Based on the FR Y-9C instructions and FR Y-14M instructions, all first lien mortgages secured by one-to-four family residential real estate located in the United States are included on the FR Y-14M, regardless of whether the loan is for a commercial purpose. Commercial loans have different historical behavior than non-commercial loans and are also frequently missing key fields necessary for modeling.[198] Instead, these loans are assigned losses separately, using a process described in more detail in Section C.ii.e.
- Loans that are not portfolio loans are removed, as these loans are not on firms' portfolios and credit losses on these loans will not impact firm provisions or capital.
- Loans reported on the FR Y-14M that are terminated (paid-off or involuntarily liquidated) in the month immediately prior to the start of the projection period are removed. As these loans have been terminated, firms no longer have ongoing exposure to additional losses on these loans.
- Government-insured loans (such as FHA or VA loans) are removed. As will be described in Section C.ii.d, the model treats firms as though they will not be responsible for losses on these loans, as they are guaranteed by the U.S. government.

Next, the models also account for missing or misreported data on the FR Y-14M report. While firms are responsible for ensuring the completeness and accuracy of data reported in the FR Y-14 information collections, the Board makes efforts to validate firm-reported data and requests resubmissions of data when errors are identified. If data quality remains deficient after resubmission, the Board would apply conservative assumptions to a particular portfolio or to

[198] For example, commercial loans where a single loan is secured by multiple properties in different states are reported with property state missing. Without property state, the model will not run.

specific data, depending on the severity of deficiencies. For example, when origination LTV is either missing, less than 0 percent, or greater than 125 percent, the Board sets these values to the 90th percentile value across all reported loans in the industry in that reporting period. When origination credit score is missing, the Board sets this value to the 10th percentile across all reported loans in the industry in that reporting period. This treatment is consistent with the Board's treatment of erroneous or missing data outlined in Section 2.9 of the Stress Testing Policy Statement.

In the cases below, missing variables are imputed in lieu of dropping the loan entirely; in general, conservative assumptions are used to fill in missing data:

- If the origination interest rate is missing, its value is imputed using other fields on the FR Y-14M, as detailed later in this section. The scoring process for these loans is described in more detail below.
- If the origination loan term is missing, the loan is treated as having an origination term greater than 30 years, as this is the more conservative category.
- If the date of initial reset is missing for ARMs, the loan is treated as having a five-year initial rate term, followed by annual interest rate resets (a "5/1" ARM). In general, shorter initial terms correspond with higher levels of default risk; while 5/1 ARMs are less common than 7/1 or 10/1 ARMs, assuming these loans to be 5/1 ARMs provides conservative estimates given missing data.
- If the reported occupancy type of the loan is missing, it is treated as owner-occupied, the most common occupancy type. More than 80 percent of loans in recent data reported on FR Y-14M, Schedule A.1 (First Lien) are marked as owner-occupied.
- The model accounts for the increased riskiness of loans returned to firm portfolios from GSE securities.[199] In a limited number of cases, information on whether a loan was returned from a GSE security may be unavailable, not due to inappropriately missing data, but because some loans reported on FR Y-14M, Schedule A have not been in the reporting population of a firm for a full 14 months[200] prior to the start of the projection period. In these cases, the First Lien PD Data from the overlapping time period are used to impute the likelihood that a loan was returned from a securitized loan to a portfolio loan based on the industry share of loans that have experienced this return over that time period. This imputation is based on loans that share similar characteristics to the loan

[199] The same imputation logic described here is used to determine whether loans were returned from private label securities. While the PD model does not incorporate whether loans were returned from private label securities, as this variable was not found to be an important predictor of delinquency, payoff, or default, such loans are excluded from the portfolio used to calculate new origination losses, described in detail in Section C.ii.d.

[200] Fourteen months is needed to cover each month of the four full quarters prior to the quarter in which a loan is reported.

with missing data. Each loan in a given segment is randomly assigned whether or not it has been returned from a GSE, and whether or not it has been returned from a private label security based on the share of loans with similar characteristics experiencing such a return in each quarter.[201] The characteristics used to assign the probability that a loan is assigned to have been returned from a GSE are as follows:

- Property state, grouped into regions generally by geographic regions.
- Loan status, grouped as follows:

1. Current or less than 29 days past due
2. 30-89 days past due
3. 90 or more days past due or in foreclosure

- Vintage, grouped as follows to avoid categories becoming too sparse:

1. 2005 and earlier vintages are combined
2. For Option ARMs, 2007 and after vintages are combined
3. 2008 and after vintages are combined if any of the following criteria are met:

- FRMs with original credit score less than 680, or ARMs with original credit score less than 720
- FRMs with original LTV above 90 percent, or ARMs with original LTV above 80 percent
- All loans greater than 30 days past due or in foreclosure

4. Otherwise, the origination year is applied directly

- Product, grouped as follows:

1. FRM
2. ARM
3. Option ARM

- Original credit score, grouped as follows (note that Option ARMs after 2007 are not separated by credit score, due to sparseness):

1. Less than or equal to 680
2. 681-720
3. Greater than 720

[201] Random assignment is used in this assumption instead of an alternative where each loan in a given segment is given a probability of having been returned from a GSE or private label securitization. Using random assignment will on average produce the same loss rate as assigning a probability, and is consistent with the definition of these variables that expect to take on values of “0” (not returned) or “1” (returned). Therefore, the random assignment method is used.

- Original LTV, grouped as follows (note that Option ARMs originated after 2007 are not separated by original LTV, due to sparseness):

1. Less than or equal to 65 percent
2. 66-80 percent
3. 81-90 percent
4. Greater than 90 percent

When certain other variables used in the model are missing, it is not possible or not reasonable to replace these variables with a conservative value. If a portion or entirety of a firm's submitted data is too deficient to produce a supervisory loss estimate, the Board assigns a high loss rate to the share of deficient portfolio balances based on supervisory projections of first lien losses for other firms. This high loss rate is based on the loss rate path of the 90th percentile firm ordered by loss rates, with the percentiles calculated based on 13-quarter losses. In the case where no firm is exactly at the 90th percentile, the loss rate path of the firm immediately after the 90th percentile is used. This approach is taken to be consistent with the principle of conservatism and is detailed in Section 2.9 of the Stress Testing Policy Statement.

The following are characteristics of loans that make it infeasible to apply the model:

- Interest rate at origination (FR Y-14M, Schedule A.1, Line Item 44) is missing or invalid (less than or equal to zero). When FRM origination interest rate is missing or invalid, it is replaced with current interest rate (FR Y-14M, Schedule A.1, Line Item 56), if available; when ARM origination interest rate is missing or invalid, it is replaced with the Initial ARM Rate (FR Y-14M, Schedule A.1, Line Item 29), if available. If none of these are available, variables such as spread at origination cannot be calculated, so the loan cannot be scored.
- Origination amount is missing or less than or equal to 0.
- Origination date is missing. Origination date is used to determine the age of the loan. Loans originated prior to 1980 are also treated as having missing origination date because of limited macroeconomic data availability before this time. Loans originated before 1980 account for an exceedingly small share of overall balance.
- If interest rate type cannot be determined, the loan cannot be identified as an FRM or ARM and cannot be run through the appropriate model.
- Next payment due date is missing or invalid. Next payment due date is considered invalid if it is earlier than the origination date. Next payment due date is used to calculate the starting payment status of the loan.

- Property state is invalid. Property state is needed to determine historical macroeconomic variables such as house price index at origination. Loans outside the 50 U.S. states and Washington, DC, are also removed. In most cases, domestic first lien balances exclude loans to borrowers in U.S. territories. These loans account for an extremely small portion of the portfolio (0.01 percent of total balances); given the small number of loans at issue, the challenges of adjusting the model to score them, including querying and validating historical macroeconomic data for these regions, outweigh the model performance improvements. Furthermore, in most cases, domestic home equity balances exclude loans to borrowers in U.S. territories.[202]

Similar to estimation data, macroeconomic data is merged in with the FR Y-14M portfolio data. The macroeconomic data is applied in the model both as of the origination date of the loan (for instance, to calculate spread at origination) as well as for each projection quarter (for instance, to calculate the percent change in HPI). Historical macroeconomic data is sourced from the same dataset that is used when estimating the model coefficients, as described in Estimation Data Cleaning and Preparation; projected macroeconomic data during the supervisory stress test scenario is sourced from the Board's Stress Test Scenarios.[203] Data are merged at a quarterly frequency. For contemporaneous data, the model's use of quarterly transitions necessitates this frequency, and aligns with the frequency used in projections. For origination data, it is possible to use monthly data instead; however, the quarterly data simplifies the process and allows for the maintenance of a smaller macroeconomic dataset to be merged in.

For macroeconomic variables that are merged at the national level (in particular, measures of interest rates), the same macroeconomic variable value is assigned to all loans in a given quarter. Unemployment rate is merged at the state level, based on the state in which the property is located. House price index is merged at the county level, when possible, based on a mapping of the reported ZIP code of the property to a county. For ZIP codes that cannot be

[202] *See* FR Y-9C instructions at 391, glossary entry for "Domestic Office."
[203] *See* Section III.B of the Enhanced Transparency and Public Accountability Proposal for additional information on certain data cleaning processes that are applied to the variables in this dataset.

mapped to a county, or for counties for which house price index is not provided,[204] the state-level house price index is used instead. This process allows for the inclusion of historic house price information at the most granular level available to ensure the model is reflective of true housing market conditions prior to the start of the projection horizon. While historic variation in state unemployment rate and state and county house price indexes are preserved, projected values of these variables under the supervisory stress test scenario are assumed to align with the national macroeconomic path. State level unemployment is assumed to have the same absolute quarter over quarter change in each quarter as the projected national level unemployment rate, while state and county house price indexes are assumed to have the same percentage quarter over quarter change in each quarter as the projected national house price index. Assuming consistent macroeconomic conditions across geographies is consistent with other models used in the supervisory stress test, to ensure that loans are not unduly penalized due to the geography in which they are located (see Section III.B of the Enhanced Transparency and Public Accountability Proposal).

Also similar to estimation data, conforming loan limits are assigned to identify "jumbo" mortgages, based on the origination year and number of units[205] of the property. As with the estimation data, the same conforming loan limit is applied to all loans secured by properties with a given number of units originated in a given year.

Payment status (current, delinquent, paid off, default, etc.) is assessed based on certain variables reported on the FR Y-14M, as described below, to align with the definition used for estimating the model. Days past due is a key variable used to determine payment status and is

[204] House price index is not reported for all counties. Generally, smaller counties with fewer housing transactions are less likely to have house price index available.
[205] In the rare case that the number of units of a property is missing, the loan is assumed to not be a "jumbo" mortgage.

calculated based on the elapsed time between the reported next payment due date (FR Y-14M, Schedule A.1, Line Item 55) and the reporting as of month date (FR Y-14M, Schedule A.1, Line Item 140). A loan is marked as delinquent if it is between 90-179 days past due or is in foreclosure, as judged when the reported code on foreclosure status (FR Y-14M, Schedule A.1, Line Item 65) is set to "1–In foreclosure, pre-sale".[206] A loan is marked as default if it is 180+ days past due; if the paid-in-full code (FR Y-14M Schedule, A.1, Line Item 64) is coded as "2–Involuntary liquidation;" or if the foreclosure status is reported as "2–Post-sale foreclosure, Redemption, non-REO" or "3–REO." A loan is marked as current if it is less than 90 days past due. A loan is marked as paid off if it is reported as a voluntary pay off (paid-in-full code is set to "1–Voluntary payoff"), and a servicing transfer if the paid-in-full code is set to "3–Servicing Transfer;" these loans are no longer on firm balance sheets once paid-off or transferred, so no losses are projected on these loans. Other loans (for instance, where loan status is "Unknown") are not modeled and given a conservative loss rate.

To identify whether a loan was repurchased from a security issued by Freddie Mac or Fannie Mae or a private label security, the model must use the previous history of the loan. This identification requires an adjustment in certain cases where a loan (or portfolio of loans) was sold from one reporting institution to another. In the case of such a sale, the Board works with the acquiring institution to maintain compatibility of loan identification numbers before and after the sale, such that the complete loan history of acquired loans can be used when possible. When this process is insufficient to identify the required history of a loan, for instance in situations

[206] Foreclosures are ignored from the logic in cases where the borrower has declared bankruptcy. This is intended to be consistent with the treatment of bankruptcy in the Mortgage Bankers Association definition of delinquency, which freezes delinquency status at the time of the bankruptcy notification until the bankruptcy is resolved. See "National Delinquency Survey," Mortgage Bankers Association, https://www.mba.org/docs/default-source/research-and-forecasts/faqs/26986-research-nds-faq-flyer.pdf?sfvrsn=6a5d82c2_1.

when the loans are acquired from an institution not reporting the FR Y-14 reports, the imputation process outlined earlier in this section is applied instead.

Some minor data manipulations are necessary to apply the model parameters to the FR Y-14M data. To align the format of the origination LTV and interest rate variables in the FR Y-14M with that of the First Lien PD Data, these fields are multiplied by 100.

Finally, the overwhelming majority of credit scores reported in the FR Y-14M follow a scale ranging from 300–850.[207] As long as scores appear to generally follow the same scales, no adjustments are made based on the vendor or version of the score used. Should a situation arise in the future where a substantial number of loans are reported using a different scale, the Board may consider making adjustments to the scores as they enter the model to ensure consistency.

Loans that are defaulted at the beginning of the projection period are not run through the model; these loans are treated separately. Loans that have not reached terminal status are fed into the Markov chain framework to produce quarterly estimates of default and payoff probability.

Treatment of Option ARM Loans

As discussed in Section C.ii.a.(1), Option ARM loans are modeled as if they are traditional ARMs, except that an adjustment is made to project the payoff rate at half of the rate outputted based on the model coefficients. This calibration is based on Board analysis that demonstrated that Option ARMs pay off at lower rates than other ARMs, and that the adjustment improves historical model fit. This treatment has a miniscule impact on the model, given the tiny share of Option ARMs in the portfolio in recent years.

[207] In the FR Y-14M instructions, firms report the origination credit score as well as the vendor and version of the score.

(4) Alternatives

Alternative Model Structures

The First Lien PD Model uses a loan-level, multi-period, state transition model approach, which projects the probability in each quarter of a loan transitioning from its existing state to one of several other states. This approach is valuable in the context of the stress test, which requires the projection of first lien mortgage loss rates over the course of a hypothetical recession.

As discussed in the review of literature in Section C.ii.a.(2), the public domain includes numerous examples of models for modeling credit events. The Board considered a wide range of approaches in determining the appropriate model.

The decision to use a loan-level model is based on the large number of loan and borrower characteristics that impact the default and payoff risk of first lien mortgages, and the availability of loan-level data reported on the FR Y-14M. There are academic studies (see Hale, Krainer, and McCarthy, 2020) that suggest that modeling using more aggregated portfolio data can produce more accurate projections. In particular, the authors of that paper suggest that using a loan-level model, along with aggregated macroeconomic data, can lead to measurement error. For instance, while the model can account for unemployment rates increasing in a given area, the stress test scenarios do not account for whether an individual borrower experienced job loss; as a result, this must be estimated based on aggregated data; in this case, the state-level unemployment rate. Despite these concerns, a loan-level approach allows for much more granular differentiation compared to a top-down approach that does not consider individual loan characteristics. Loan-level models are widely applied in academic and industry contexts,[208] and the large body of literature provides useful context for developing an accurate, robust model of first lien PD.

[208] *See* the review of literature in Section C.ii.a.(2).

Relying on a loan-level approach is particularly valuable in the context of the supervisory stress test, as an aggregate approach, while producing reasonable industry-level results, may struggle to capture important variation across firms in projecting default rates. Given the availability of granular data, the Board therefore chooses to use a loan-level approach.

The determination to use a multi-period model, as opposed to a single-period model, is necessitated by the design of the supervisory stress test. The supervisory stress test uses quarterly loss estimates to produce projections of the balance sheets of covered institutions over a nine-quarter horizon. This substantially limits the utility of model structures that produce a single estimate of losses, rather than a path. The chosen multi-period transition model approach provides quarterly projections of default and payoff rates, allowing projections of not just the total default rate but its trajectory.

Additionally, consistent with the mortgage literature, the competing risks of default and payoff are considered. While this approach adds complexity to the model, it significantly improves model accuracy. Prepayment rates vary for mortgages depending on the macroeconomic environment and characteristics of the loan; the modeling approach allows for these factors to be internalized in the model. Payoff rates are further used in the supervisory stress test context to determine the amount of run-off balance, which is used to determine the level of new originations.[209]

Given these choices, the Board considered other model structures for projecting a multi-period, semi-annual model, in addition to a state transition model. These alternatives are reviewed in detail in the review of literature in Section C.ii.a.(2). To recap, key alternatives

[209] The supervisory stress test assumes that a firm's balance sheet will remain constant throughout the projection period; new origination balances are set to be equivalent to the sum of loss balance and payoff balance in a given quarter. For more information on the new origination process, see Section C.ii.d. The constant balance sheet assumption is discussed further in Section A of the Aggregation Models Documentation (Balances Model).

include a simple multinomial logit approach or a hazard model approach. A simple multinomial logit approach is less appealing as without flexibility for loans to shift into an intermediate delinquent state, it is less predictive of default risk in a multi-period setting. A hazard approach is valuable for its ability to incorporate unobserved differences between loans. It also maximizes simplicity and minimizes the Board's operational challenges compared to a transition model, especially for considering the past payment statuses of loans in the model (such as previous delinquency). However, it does not allow for tracking of loans through the different transition payment statuses, which update dynamically, which is important to account for the shape and persistence of the contemplated macroeconomic shock. Given these factors, and consistent with many industry applications, the state transition model framework is used rather than alternative approaches.

Alternative Covariates

A review of literature and consideration of the Board's experience and expertise led to the consideration of a large number of variables for inclusion in the model. This section describes alternative specifications of the transition equations and the determinations that led to the alternatives not being chosen. Broadly, the variable choices are made to maximize economic support and statistical fit (as discussed in Section C.ii.a.(2)) while ensuring that the model was sufficiently simple, which, as explained in the Stress Testing Policy Statement, allows for a more straightforward interpretation of the drivers of model results and minimizes operational challenges for model implementation.

In cases where the above considerations do not provide a clear best option, and multiple options appear to be equally sound, the Board relies on the stress testing principles to determine the appropriate model, consistent with the Stress Testing Policy Statement. For instance, the

Board considers the principle of simplicity to allow for a more straightforward interpretation of the drivers of model results and to minimize operational challenges for model implementation. The Board also considers the principle of conservatism to select the model that produces higher loss estimates, if multiple approaches are equally sound.

The Board considered simplifying the transition equations, particularly the transitions from current that have a large number of variables, to reduce the number of covariates and make changes to model projections more easily interpretable. However, all variables in the transitions provide sufficient explanatory power to justify inclusion.

In addition to simplifications, the Board considered for inclusion in the model other variables that are not included in the final model specification, outlined below:

- Current credit score: While the model already accounts for the borrower credit score at origination, including the refreshed credit score could improve the precision of the model estimates. Credit score generally increases over the life of the mortgage as borrowers make their regular payments, although it can decrease in certain cases due to borrower behavior on other loans outside of the mortgage. Despite the potential advantages of including current credit score, it is not well populated in the First Lien PD Data, particularly in the early periods of the historical data. Given these constraints, the Board determined that relying on origination credit score as a reasonable proxy for borrower risk.
- Documentation type: This term would account for differences in the income verification process across mortgages, as some loans have full verification of income, assets, and other underwriting criteria and others have little or no documentation. Loans where the verification process is less stringent have a higher chance of default, as without verification it's possible that income or assets reported at origination are incorrect. Despite the potential advantages of including this term, the coverage in the First Lien PD Data is insufficient for use in the model. Therefore, it is not included. This term, as well as other loan characteristics, are partially accounted for by the inclusion of spread at origination, which takes into account that lenders will charge higher interest rates to more risky borrowers.
- Debt-to-income (DTI) ratio: This is the ratio of the borrower's monthly debt payments to the borrower's gross monthly income, generally calculated at origination. Higher DTI is associated with non-payment, as borrowers more burdened by payments are more likely to become delinquent, especially during times of economic stress.[210] However, this

[210] See Jagtiani, J. and W.W. Lang (2011). "Strategic Default on First and Second Lien Mortgages During the Financial Crisis," Journal of Fixed Income, Spring, 7-23.

variable is not ultimately used due to insufficient data coverage, as it is frequently unavailable in the First Lien PD Data.

- Refreshed property value: In certain circumstances, a property may be appraised following the origination date, providing updated information on the value of the property. This may occur in circumstances where the property value has changed significantly, separate from broader changes in market housing prices. However, one concern with using refreshed property value information is that the population of loans with updated appraisals are not necessarily representative of the entire portfolio; using refreshed property values could lead to differential treatment based solely on whether or not there was a new appraisal of a property since origination. Given these potential risks, the Board does not incorporate refreshed property value into the PD model.
- Previous delinquency: Among current loans, loans that have previously been delinquent are more likely to fall behind on payments again. Similarly, loans that remain in delinquent status for multiple quarters are less likely to eventually default than loans that recently became delinquent, as the former category of loans has shown active efforts to avoid default. To account for this, the Board considered including previous delinquency status in the model. However, this is made challenging by the model implementation using a Markov chain, which assigns a probability of a loan being current or delinquent in each quarter. Because it is not clear during the projection horizon whether a current loan has continuously been current or had been delinquent earlier in the projection horizon, it is challenging to apply a previous delinquency variable that can change dynamically over the projection horizon in the model, without substantially increasing complexity. Additionally, analysis performed by the Board demonstrated that while previous delinquency is an important predictor of nonpayment at the loan level, the inclusion of previous delinquency has minimal impact on projections at the industry level, as current loans that have previously been delinquent are uncommon. For these reasons, previous delinquency is not included in the First Lien PD Model.
- Borrower income or borrower savings: Since borrowers rely on income—and when income is unavailable, savings—to make payments, it is likely that including a borrower's income and savings in each quarter would improve the projection of PD. However, borrower income and savings levels are not available dynamically in either the First Lien PD Data or the FR Y-14M data, and collecting these data would be challenging and burdensome. Therefore, these variables are not included in the model.

Additionally, the Board considered a variety of options in determining how to incorporate data from the COVID-19 pandemic period in the model. As discussed in Section C.ii.a.(2), without any adjustment, historical relationships between house prices and default break down due to the widespread availability of forbearance programs and other government support during this period. The model accounts for this period using a term to account for the industry share of portfolio loans at large banks that were in forbearance at the end of each quarter. Alternatively, the Board could account for forbearance at the loan level by identifying individual loans in forbearance. However, this approach would require the Board to obtain data with the complete forbearance history of each loan.

While the loan-level term did produce slightly more precise model estimates compared to the chosen industry-level term, the Board does not use this approach. While forbearance occurs outside of the COVID-19 pandemic period, it is generally less widespread and tends to have more restrictive conditions. Therefore, the forbearance variable is only used to account for historical behavior, rather than to predict future behavior of loans in forbearance. Given this and the similar model outcomes under either method, the Board determined that the more parsimonious solution using the industry share of forbearances is appropriate when compared to the model incorporating forbearance at the loan level.

The Board also considered incorporating loan modifications, which can be used by firms to manage loans that become delinquent. Ultimately, the Board determined that directly accounting for modification is not necessary, as the model already implicitly captures the effects of loan modification and evolving modification practices in the probability that a delinquent loan returns to current status (the delinquent-to-current equations).

The Board considered additional alternative specifications of the six transition equations from delinquent. While many of the same variables that impact transitions from current also conceivably impact transitions from delinquent, the equations are estimated with fewer variables. Furthermore, the transitions from delinquent tend to have worse overall performance compared to the transitions from current. However, a simpler approach was chosen for a handful of reasons. Most notably, transitions from delinquent are observed more rarely in the data, leading to a sparser estimation dataset. With sparser data, inclusion of too many variables can lead to noisy and unreliable estimates. This can be partially accounted for by over-sampling delinquent loans; however, even with a larger sample, model fit did not substantially change. Additionally, the transitions from delinquent are less systematic than transitions from current; this makes modeling these transitions challenging regardless of data constraints or number of variables included.[211]

Macroeconomic characteristics are included in the model to account for increases in First Lien PD rates during stress periods. House prices, unemployment rate, and various interest rate indicators are included in the model. As unemployment rate is used as a broad proxy for economic stress and households' ability to pay bills, the Board considered other indicators of economic strength such as disposable income and real GDP growth as well. Ultimately, unemployment rate was sufficient to account for household economic conditions.

Alternative measures of unemployment rates were considered. Notably, the Board tested incorporating the deviation of the unemployment rate from its long-term average value, where the long-term average is defined as the average unemployment rate in a given state from July 1990 to November 2007. This term could improve model predictive power by accounting for persistent state-level differences in average unemployment rate. However, the Board determined that including this term did not improve statistical metrics of model performance; furthermore, using a more complex transformation of unemployment rate could make interpretation of the unemployment effect harder to explain compared to the percentage point change in unemployment rate.

[211] In general, research on the factors that lead delinquencies to progress to default is sparser than that of predicting initial delinquency. Gardner et al (1989) provide valuable research on this issue. Gardner, Mona J., Dixie L. Mills and John Gardner, "Evaluating the Likelihood of Default on Delinquent Loans," Financial Management 18 (1989): 55.

The model takes into account variation in historical house price index and unemployment rate by applying house price indexes at the county level (state level, if county level is unavailable) and by applying unemployment rate at the state level. For house price index, the model uses county-level data to account for the local nature of housing markets. For unemployment rate, the Board considered using county-level variation but determined that state level variation was a more stable indicator of household labor market conditions. Because labor market conditions tend to be regional, county-level unemployment rate may not accurately reflect the labor market conditions faced by an individual in that county; at higher levels of geography, such as states, this is less likely.

With respect to interest rates, a wide range of inputs were considered for inclusion in the model, including both long- and short-term interest rate variables, to capture different effects. Due to the difference in incentives between FRMs and ARMs, interest rates are discussed separately for the two product types.

Because FRM payments do not adjust with changes to interest rates, changes to market interest rates from origination do not meaningfully impact the risk of nonpayment. The spread at origination, defined as the difference between the origination interest rate of a loan and the 10-year yield in the month of origination, is used to account for otherwise unobserved differences in loan risk among FRMs in the current-to-delinquent transition; the 10-year Treasury yield is used as a proxy for the risk-free long-term interest rate available in the market. A larger spread suggests that the lender is demanding a larger interest rate to cover the increased riskiness of a loan. Meanwhile, in the transition from current to payoff, changes to interest rates are more fundamentally important, as they define a borrower's incentive to refinance. In general, borrowers are more likely to pay off when they can refinance their loan into a new loan with a lower interest rate, and therefore a lower monthly payment. This effect is proxied with the difference between the average 30-year fixed-rate mortgage interest rate (determined by the Primary Mortgage Market Survey of the Federal Home Loan Mortgage Corporation) in origination compared to that of a given period. Again, a long-term rate is used here given that fixed-rate mortgages have lengthy terms; the 30-year fixed-rate mortgage rate provides the best proxy for what a borrower can expect to pay in the case of refinance. While other interest rates, such as the 10-year Treasury yield, were considered as well, the chosen rate was selected for its representativeness. To account for any impacts on FRM payoff rates from short-term yields, the slope of the yield curve (defined as the 10-year Treasury yield minus the 3-month Treasury yield) is included as well; however, this is notably less impactful in the equation. In particular, projected payoff rates in the model do not vary significantly as the slope of the yield curve changes within its historical range when compared to the impact of changes in the spread over of the 30-year fixed mortgage rate.

The behavior of ARMs is different, for multiple reasons. First, because interest rates on ARMs regularly reset, changes in interest rates are directly associated with nonpayment, as a higher interest rate means a higher payment for the borrower. Second, unlike FRM rates, which tend to be correlated with long-term rates, ARMs are also correlated with short-term rates, as the adjustments in interest rates are generally contractually based on changes in short-term rates. Similar to FRMs, the spread at origination is calculated based on the 10-year Treasury yield, to account for differences in risks of loans that are otherwise unobserved. Additionally, though, the ARM current-to-delinquent equation accounts for the change in the 3-month Treasury yield since origination to proxy for changes to the required payment. A higher 3-month Treasury yield is associated with higher rates of nonpayment. One consideration is that many ARMs have long periods (3, 5, 7, or 10 years) for which the interest rate is held fixed before the interest rate begins to float; during the initial rate period, ARMs behave more similarly to FRMs. Therefore, the impact of changes to interest rates from origination is limited in the model to loans that have reached the first reset period. Changes in shorter-term rates rather than longer-term rates are considered in this term to reflect the most common contractual terms of ARMs.

In contrast to the current-to-delinquent equation, the ARM current-to-payoff equation is sensitive to both short- and long-term interest rates. The reason for the sensitivity to short-term interest rates is similar to the reasoning in the current-to-delinquent equation; in particular, once the interest rate of an ARM begins to float, increases in interest rates lead to higher monthly payments, increasing incentives to payoff. However, in the current-to-payoff equation, ARMs are also sensitive to changes in long-term rates. This is because borrowers generally have the outside option of refinancing their loan into a FRM, which is more incentivized when FRM rates are lower. To account for this outside option, the model incorporates the difference between the current interest rate on the ARM and the average 30-year fixed-rate mortgage interest rate (as used in the FRM equation). When this spread is higher, borrowers have more of an incentive to refinance into an FRM. Due to the incentives and the widespread availability of FRMs, long-term interest rates are applicable in the ARM current-to-payoff transition in addition to the short-term rates used in the current-to-delinquent transition.

In sum, the Board considered interest rates across different maturities throughout the model. The final specifications are chosen to align with economic theory and are confirmed by ensuring the coefficients in the model are in the expected direction. The sensitivity of ARMs to interest rates is more robust compared to that of FRMs, given that interest rates on ARMs reset with changes to market rates.

Finally, in addition to different direct implementations of macroeconomic variables, the Board considered alternative transformations of other variables included in the model: in particular, updated LTV. As previously discussed, updated LTV is calculated based on the origination LTV and the change in house prices since its origination. An alternative implementation could also account for changes in the balance of the loan since its origination, which generally declines as the loan amortizes. Accounting for amortization in the PD model would reflect that as borrowers pay down their balance, they have more equity in their homes, reducing the risk of default. Nevertheless, the Board does not account for amortization in the PD model, despite these potential benefits. The impact of amortization is limited for most loans, as amortization tends to account for a small share of the original balance for most loans, reflecting that most loans prepay long before they are scheduled to mature. Additionally, not accounting for amortization avoids the need to model changes to principal balance through the projection period, which would substantially increase model complexity. Finally, while certain loans with more or less amortization would see different projections if the model were to account for amortization, the average impact would be small. This is because the definition of updated LTV is consistent between the estimation of the model coefficients and the projection of PD. In that sense, the coefficients on updated LTV implicitly account for the possibility that the balance of the loan may have decreased from origination. While this may lead to imprecise estimates at the loan level, these differences average out at the industry level, leading to reasonable loss estimates.

Alternative Data Sources

The First Lien PD model coefficients are calibrated using the First Lien PD Data, a loan-level dataset comprised mainly of the servicing portfolios of the largest residential mortgage servicers in the U.S. An alternative source that could be used to fit the model parameters is the FR Y-14M report itself,[212] which is reported monthly by FR Y-14 reporters with material first lien portfolios.

One advantage of the FR Y-14M data is that the loan population is representative of the population of loans on which the supervisory stress model is used to project losses. Since the First Lien PD Data may include loans from certain lenders who are not FR Y-14 reporters and may not include loans from certain lenders who do report on the FR Y-14, the loan population in the First Lien PD Data may not be reflective of the loan population for which the model is used to project losses. If the loan characteristics vary in ways that are not observed or included in the model, this could cause inappropriate loss projections.

Despite this representativeness concern, the First Lien PD Data is used due to its longer time series. The FR Y-14M coverage does not begin until June 2012, limiting the visibility these data provide into the behavior of home equity products during the 2008 financial crisis period, the most significant stress event in the housing market in recent memory. These periods are crucial for estimating the impacts of falling house prices on performance.

To assuage representativeness concerns, the Board performed analysis of key fields in overlapping periods between the First Lien PD Data and the FR Y-14M data and found that, in the Board's qualitative judgment, they were generally similar.[213] While minor differences are observed, the distributions are aligned well and are comparable for the purposes of applying the model to the firms in the Y-14M. The Board has also performed preliminary testing on an alternative model where the First Lien PD Data and the FR Y-14M data are combined and jointly

[212] Specifically, Schedule A.1, which is comprised of first lien loan-level data.
[213] Among overlapping periods, the FR Y-14M data aligns well with the First Lien PD Data on key indicators such as origination credit score and origination LTV.

used to fit the model parameters. The preliminary analysis indicated that this alternative specification would likely lead to small differences in model coefficients, given the similarities between the datasets, and are unlikely to impact stress test results. Because of the small expected changes and the complexity of combining the datasets, the Board determined that combining the datasets is not appropriate at this time. Despite this finding, the Board may in the future use the combined dataset to improve data representativeness while ensuring coverage of the 2008 financial crisis period. In the meantime, the Board regularly compares key variable statistics between the two datasets to ensure continued representativeness of the First Lien PD Data.

(5) Questions

Question C1: The Board is seeking comment on the treatment of the origination vintage variables for loans originated in and after 2009 when projecting First Lien PD in the supervisory stress test. Should the Board consider modifying or eliminating this treatment of the origination vintage variables for originations in and after 2009? If the Board were to eliminate this assumption, how should the Board address concerns about the uncertainty of the behavior of such loans during an economic downturn, in line with the principle of conservatism from the Stress Testing Policy Statement?

Question C2: The Board is seeking comment on the decision to treat default as a terminal state in the model, as opposed to an alternative assumption that would allow defaults to cure.

Question C3: The Board is seeking comment on whether the First Lien PD Model should continue to rely on original loan balance when computing updated loan-to-value ratio, as opposed to an alternative under which this variable would adjust based on changes in loan balance since origination.

Question C4: The FR Y-14M instructions allow firms to report a variety of commercially available credit scores. While this provides flexibility to reporting institutions, it raises concerns that if the same credit score value is associated with different risk levels for credit scores taken from certain vendors or certain versions, the model may produce inappropriately high or low PD projections. How should the Board accommodate the inclusion of different credit scores while avoiding inappropriately favoring or penalizing loans reported with certain credit scores?

b. Loss Given Default Model

(1) Description

The First Lien LGD model projects the percent of loan balance that a lender would not be able to recover after a borrower enters default. When a borrower enters default, the lender can often recover a portion of the value of the loan via proceeds from the sale of the collateral or other sources.

The LGD model is run in two stages. In the first stage, the length of time projected to elapse between default and liquidation is assigned. This length of time is calibrated for all loans as 22 months, based on historical First Lien PD Data[214] on loans that defaulted and liquidated, as detailed in Section C.ii.b.(2). In the second stage, this timeline is used as an input to a regression model used to calculate the loss severity (the "loss severity" model). The loss severity model is made up of three equations, corresponding to "Prime", "Alt-A", and "Subprime" loans, where the categorizations are determined based on characteristics of the loan.[215] In particular, the mapping is defined in Table C5.

[214] The data used in this calculation is the same as the data used to estimate the PD model parameters.
[215] These categorizations are referred to as "credit classes," and are made algorithmically due to lack of reported categorizations of Prime/Alt-A/Subprime in portions of the data used to fit the model parameters. Further support for these categorizations is available in Section C.ii.b.(2).

Table C5 - Definition of Credit Class in the First Lien LGD Model[216]

	Origination Credit Score				
Origination Loan-to-Value Ratio	Under 620	620-659	660-699	700-759	760
80 or lower	Subprime	Alt-A	Prime if full doc Alt-A if not	Prime	Prime
Above 80	Subprime	Subprime	Alt-A	Alt-A	Prime

Note that in addition to this table, loans marked as Option ARM loans are modeled as Alt-A loans, regardless of other features. This choice is consistent with the stress testing principle of simplicity, based on the Board's expertise and experience; Option ARM flags can be negative amortizing loans, which were marketed to Alt-A borrowers in the lead up to the 2008 financial crisis. Because Option ARM loans account for less than 2 percent of loans reported in the FR Y-14M data as of December 2024, the treatment of option ARM loans does not meaningfully impact stress test results.

A separate equation is then estimated, separately for each collateral type, as specified in Equation C2.

Historical data on first lien mortgage recoveries is less widely available than on the frequency of mortgage defaults. Mortgage data collected from servicers, like the First Lien PD Data, tend not to include reliable information on the amount of the recovery of loans; additionally, while recovery information is available on the FR Y-14M, the FR Y-14M does not include data during the 2008 financial crisis, a key period of stress in the housing market that is

[216] Origination loan-to-value is characterized based on the reported value in FR Y-14M, Schedule A.1, Line Item 8 (Original LTV). Origination credit score is based on the reported value in FR Y-14M, Schedule A.1, Line Item 13 (Origination Credit Bureau Score). A loan is "full doc" if the value reported on FR Y-14M, Schedule A.1, Line Item 10 (Income Documentation) is set to "1" (for "Full"). Despite the recognition of the limited coverage of the documentation variable in the First Lien PD Data described in Section C.2.a.(4), coverage is sufficiently comprehensive in the data used to estimate the loss severity model.

important for projecting first lien losses under stress. Therefore, to estimate the loss severity model, the Board relies on two sources of historical data on first lien mortgage losses:

- Historical data on liquidated mortgages in non-agency mortgage-backed securities (referred to in this document as private-label securities, or the "PLS data"), collected by a third-party vendor.
- Historical data on liquidated mortgages in mortgage-backed securities guaranteed by a GSE from a public source (the "GSE data").

While each of these datasets uses mortgages that are securitized, rather than held on banks portfolios, the use of the two datasets captures a large share of the domestic housing market. To account for the possibility that characteristics of the loans reported in the PLS and GSE data may differ from the loans reported on the FR Y-14M, observations are re-weighted, by data source and collateral type, to as closely as possible match the observable characteristics of the FR Y-14M data. When setting the weights, the Board considered five features that reflect fundamental characteristics of the loan:

- The interest rate type (ARM or FRM)
- Whether the loan purpose was a purchase or a refinance
- Whether the loan is collateralized by an investment property (as opposed to other occupancy types, like owner-occupied)
- Whether the loan is in a state with a judicial foreclosure regime[217]
- Whether the original loan balance was less than $200,000

In the PLS data, loss severity, for each loan, is defined as the share of the final balance of the loan that was charged off net of any servicer advances, as calculated based on the description

[217] Judicial foreclosure refers to a process where foreclosures go through court proceedings. Many states have processes to allow lenders to foreclose on the property without going through court proceedings (non-judicial foreclosures). Historically, loss severity has been higher in states with judicial foreclosure compared to states with widely-used non-judicial foreclosure options. When projecting first lien losses, the model treats all loans identically, regardless of the foreclosure type in the state of the loan, to avoid unduly penalizing loans in certain states. However, accounting for the share of loans in each foreclosure regime is important to produce reasonable model parameter estimates. States are defined as judicial or non-judicial in line with Cordell and Lambie-Hanson (2016).

in Section C.ii.b.(3). In the GSE data, loss severity, for each loan, is defined as the recovery rate subtracted from one, plus accrued but unpaid interest. The recovery rate is defined as the net recovery divided by the last reported unpaid principal balance, where the net recovery is calculated as the net proceeds from the sale of the property (the sale price minus expenses related to the sale), minus any expenses related to the property (e.g. taxes, insurance, maintenance), plus any other recoveries, with the exception of mortgage insurance recoveries. Note that throughout the loss severity model, recoveries from mortgage insurance are not considered in the projection of loss severity.

Based on the combined PLS/GSE data, the Board estimates the share of the loan balance at default that is expected to be recovered. Mathematically, the framework used to estimate this share is a weighted least squares regression, where the weight on each loan is determined as described above to align the characteristics of the PLS/GSE data with that of the FR Y-14M data. Weighted least squares is a version of a linear regression where each observation is weighted. Similar to other linear regression approaches, the coefficient on a given variable in a weighted least squares regression can be interpreted as the change in the outcome (in this case, loss severity) expected given a one-unit change in the value of the variable. The model parameters are estimated separately for loans characterized as Prime, Alt-A, and Subprime.

Finally, while the model can theoretically output any value as the loss severity, the Board assumes that loss severity will be no less than 0 (no recoveries greater than the outstanding balance) and no greater than 1.5 (losses cannot be more than 150 percent of the outstanding balance). In particular, the Board assumes that the loss severity is 0 for all loans where the model outputs a loss severity of less than 0; and the Board assumes that the loss severity is 1.5 for all loans where the model outputs a loss severity of greater than 1.5. These assumptions ensure reasonable loss severity estimates for all loans. The restriction that loss severity will not be less than 0 is in line with the stress testing principle of conservatism; while some loans do historically have recoveries exceeding the balance owed, it is unusual and unlikely to occur in a period of economic stress. The restriction that loss severity cannot be more than 1.5 is for reasonableness and to avoid results driven by outliers. A value of 1.5 is used, rather than 1, to reflect that losses can exceed balance owed; for instance, if the costs of maintaining and selling the property exceed the proceeds from the sale. However, while some additional losses are plausible, the Board, based on its experience and expertise, determined that values above 1.5 are unusual (in the historical PLS and GSE data, less than 1 percent of liquidations had LGD above 1.5) and may reflect data errors or outliers. Additionally, the linear regression approach makes the model susceptible to outliers; for instance, a single loan with an erroneously reported 50,000 loss severity could impact coefficients for the entire model. The Board determined that a value of 1.5 was appropriate to account for loans with high loss severity while avoiding contamination by outliers that could unduly affect model parameters.

The model parameters are shown in Table C6. Note that in addition to the below parameters, the Board incorporates a variable when estimating the regression to identify whether an observation came from the GSE or PLS data, to account for unobservable differences in loss severity between the two datasets. This variable is not used when projecting loss severity; instead, the model implicitly assumes that defaulted loans during the stress test will behave similarly to loans from the PLS sample. Additional details on this assumption are available in Section C.ii.b.(2).

Table C6 - First Lien LGD Model Coefficients

		Prime		Alt-A		Subprime	
Parameter	**Variable Description**	**Estimate**	**Std.Err.**	**Estimate**	**Std.Err.**	**Estimate**	**Std.Err.**
Intercept		0.4707	0.0015	0.5493	0.0017	0.5589	0.0037
Property type	Property type	-	-	-	-	-	-
	Condo	-0.0113	0.0009	0.0043	0.0006	0.0137	0.0011
	Multi-unit	0.1376	0.0013	0.1273	0.0009	0.1312	0.0024
	Planned unit development (PUD)[218]	-0.0657	0.0007	-0.0644	0.0005	-0.0500	0.0010
Origination credit score	Credit score at origination	-	-	-	-	-	-
	Flag for >720	-	-	-0.0031	0.0006	-0.0042	0.0007
Judicial foreclosure state[219] indicator	Flag whether state uses a judicial foreclosure regime	0.0348	0.0005	0.0384	0.0004	0.0365	0.0008
Origination LTV	Origination LTV	-	-	-	-	-	-
-	Flag for <=65	-0.0704	0.0013	-0.0482	0.0009	-0.0451	0.0013
-	Flag for >80	0.0298	0.0006	0.0064	0.0005	0.0087	0.0018
Updated LTV at liquidation	Original LTV, adjusted to account for changes in balance from origination and scaled by the change in house price index since origination	0.0043	0.0000	0.0042	0.0000	0.0044	0.0000
Change in HPI over	Percentage change in	-0.4867	0.0027	-0.2707	0.0021	-0.0765	0.0043

[218] *See* FR Y-14M, Schedule A.1, Line Item 23 ("Property Type") for a definition of this term.

[219] As previously described in this document, judicial foreclosure refers to a process where foreclosures go through court proceedings. Many states have processes to allow lenders to foreclose on the property without going through court proceedings (non-judicial foreclosures). Historically, loss severity has been higher in states with judicial foreclosure compared to states with widely-used non-judicial foreclosure options. When projecting first lien losses, the model treats all loans identically, regardless of the foreclosure type in the state of the loan, to avoid unduly penalizing loans in certain states. However, accounting for the share of loans in each foreclosure regime is important to produce reasonable model parameter estimates. As in the First Lien PD model, states are defined as judicial or non-judicial in line with Cordell and Lambie-Hanson (2016).

		Prime		Alt-A		Subprime	
previous year as of liquidation	house price index compared to one year prior of liquidation date						
Indicator for liquidations occurring after September 2010	Flag for if primary residence liquidation occurs after 2010 Q3	0.1125	0.0006	0.0622	0.0005	0.0421	0.0010
Loan purpose	Flag whether loan is refinance	-	-	-	-	-	-
-	Cash-out refinance	0.0664	0.0005	0.0571	0.0004	0.0723	0.0009
-	Other refinance	0.0604	0.0006	0.0490	0.0005	0.0563	0.0010
Occupancy type	Occupancy type	-	-	-	-	-	-
-	Secondary residence	0.0752	0.0017	0.0515	0.0010	0.0827	0.0018
-	Investment property	0.1085	0.0010	0.0923	0.0007	0.1271	0.0016
Loan size	Origination amount	-	-	-	-	-	-
-	Linear term from 0 to $100,000	-0.0580	0.0002	-0.0592	0.0002	-0.0614	0.0004
-	Linear term from $100,000 to $200,000	-0.0171	0.0001	-0.0151	0.0001	-0.0155	0.0001
-	Linear term from $200,000 to $400,000	-0.0039	0.0001	-0.0032	0.0000	-0.0031	0.0001
-	Linear term from $400,000 to $600,000	-0.0015	0.0001	-0.0024	0.0001	-0.0021	0.0001
-	Linear term from	0.0003	0.0002	0.0004	0.0000	0.0006	0.0000

		Prime		Alt-A		Subprime	
	$600,000 to $1.945M						
Liquidation Timeline[220]	Time between loan reaching 90 days past due and liquidation	-	-	-	-	-	-
-	Linear term from 0 to 24 months	0.0097	0.0000	0.0091	0.0000	0.0062	0.0001
-	Linear term from 24 to 48 months	0.0047	0.0001	0.0038	0.0000	0.0029	0.0001
-	Linear term from 48 to 60 months	0.0084	0.0001	0.0079	0.0001	0.0037	0.0003
Origination year	Origination year	-	-	-	-	-	-
-	2006	0.0258	0.0006	0.0222	0.0005	0.0084	0.0009
-	2007	0.0332	0.0007	0.0402	0.0006	0.0262	0.0009

The Board assumes that the last eight months of the liquidation timeline are allocated to the period during which the property becomes real estate owned, based on literature, as further discussed in Section C.ii.b.(2). A property becomes REO when a lender repossesses a loan, until the property is disposed of in a sale. Net losses on loans in REO status are treated as other real estate owned (OREO) expenses, which are a component of pre-provision net revenue (PPNR). For all loans in the LGD model, the share of the losses allocated to first lien credit losses is based on the proportion of time that a delinquent loan spends not in REO. The time not in REO is defined as the number of months between when the loan is last current and the time of liquidation, minus the number of months in REO. Mathematically, this is calculated based on Equation C5:

[220] Liquidation timeline in these equations refers to the time elapsed between when a loan reaches 90 days past due and when it liquidates, instead of the time elapsed between default and liquidation, as used previously.

Equation C5 - Allocation of First Lien Losses

$$Credit\ Loss\ Share = \frac{Timeline + 6 - 8}{Timeline + 6}$$

where "timeline" is calibrated to 22 months as noted above, the projected elapsed time between default and liquidation, the "6" accounts for the time between when the loan is last current and when it reaches default, and the "8" reflects the estimated REO portion of the timeline.[221] The remaining share of losses are designated as OREO expenses and, to the extent that they fall within the 9-quarter projection horizon, accounted for through PPNR (non-interest expense).

(2) Support for Model Decisions

The design and specification of the First Lien LGD model is supported by a review of the relevant literature and industry best practices, statistical fit, and the Board's experience and expertise. This section describes both the support for the overall model design as well as the specific variables and transformations included in the model.

Review of Literature

Like the First Lien PD model, the First Lien LGD model is informed by a review of academic literature. While literature on LGD is more limited than that of PD, due to data unavailability, the Board draws on the available materials in the public domain to develop a reliable model for use in the supervisory stress test.

Most academic research on LGD adopts linear regressions estimated with ordinary least square. For example, Lekkas, Quigley, and Van Order (1993)[222] regressed loss severity rates on original LTV, loan age, coupon spread, and a flag for loans in the state of Texas state using

[221] *See* Section C.ii.b.(2) for support for the assumption that the REO portion of the timeline is 8 months.
[222] Lekkas, V., J. M. Quigley, and R. Van Order. 1993. Loan loss severity and optimal mortgage default. Journal of the American Real Estate and Urban Economics Association 21 (4): 353–371.

approximately 9,000 Freddie Mac defaulted loans. Other studies including Wilson (1995)[223], Crawford and Rosenblatt (1995)[224], Berkovec et al. (1998)[225], DeFranco (2002)[226], Pennington-Cross (2003), Calem and LaCour-Little (2004)[227], Capozza and Thomson (2005)[228], Qi and Yang (2009)[229], and Leow and Mues (2012)[230], use similar model structures.

While ordinary least square regressions are popular due to their simplicity and interpretability, they carry an implicit assumption that the residuals are normally distributed, which may not hold in practice. One alternative can be found in Tong, Mues, and Thomas (2013)[231], which uses a zero-adjusted gamma approach to estimate a model using data in the UK. Outside of the first lien mortgage space, corporate debt LGD studies also observe that loss severities tend to be bi-modal (either most of the balance is recovered or very little of it is) and are generally between 0 (full recovery) and 1 (no recovery); to account for this, they use other model types, such as the beta regression, fractional response regression, and non-parametric methods. See, for example, Qi and Zhao (2011)[232].

223 Wilson, D. G. 1995. Residential Loss Severity in California: 1992-1995. Journal of Fixed Income 1995 (December): 35-48.
224 Crawford, G., & Rosenblatt, E. 1995. Efficient Mortgage Default Option Exercise: Evidence from Loss Severity. Journal of Real Estate Research, 10(5), 543–555, https://doi.org/10.1080/10835547.1995.12090809.
225 Berkovec, J. A., G. B. Canner, S. A. Gabriel and T. H. Hannan. 1998. Discrimination, Competition, and Loan Performance in FHA Mortgage Lending. Review of Economics and Statistics, 80(2): 241-250.
226 DeFranco R. 2002. "Modeling Residential Mortgage Termination and Loss Severity Using Loan Level Data," University of California, Berkeley Dissertation.
227 Calem, P. S. and M. LaCour-Little. 2004. Risk-based Capital Requirements for Mortgage Loans. Journal of Banking and Finance 28, 647–672.
228 Capozza, D. and T. Thomson. 2005. Optimal Stopping and Losses on Subprime Mortgages. Journal of Real Estate Finance and Economics 30(2): 115–131.
229 Qi, M., and X. Yang. 2009. Loss Given Default of High Loan-to-Value Residential Mortgages. Journal of Banking and Finance 33: 788–799.
230 Leow M. and C. Mues. 2012. Predicting Loss Given Default (LGD) for Residential Mortgage Loans: A Two-Stage Model and Empirical Evidence for UK Bank Data. International Journal of Forecasting 28: 183-195.
231 Tong E. N.C., C. Mues and L. Thomas. 2013. A Zero-Adjusted Gamma Model for Mortgage Loan Loss Given Default. International Journal of Forecasting 29: 548-562.
232 Qi, M. and X. Zhao. 2011. Comparison of Modeling Methods for Loss Given Default. Journal of Banking and Finance 35: 2842-2855.

Since the 2008 financial crisis, there have been significant developments in public-facing work on first lien LGD; a notable boost was provided by the public release of data on mortgage-backed securities guaranteed by Freddie Mac and Fannie Mae. For example, Goodman and Zhu (2016)[233] tabulated loss severity rates of defaulted Freddie Mac conventional conforming loans by LTV, credit score, vintage, and size, and compared the actual loss severity rates with those presumed in Freddie Mac's initial Credit Risk Transfer (CRT) deals.

The data also has been used to identify changes in the foreclosure process over time and across geography. In particular, An and Cordell (2017[234]; 2019[235]) incorporated liquidation timelines as a key explanatory variable in the LGD model and identified regime shifts in LGD due to structural and legal changes in the mortgage market following the 2008 financial crisis.[236] These structural changes made it more time-consuming and more costly for servicers to foreclose on properties, increasing loss severity rates. With respect to geography, Cordell and Lambie-Hanson (2016)[237] found that the increases in liquidation timelines after the 2008 financial crisis were concentrated in states with judicial foreclosure processes.

[233] Goodman, Laurie, and Jun Zhu. 2016. Loss Severity on Residential Mortgages. Journal of Fixed Income 25(2).
[234] An, X. and L. Cordell. 2017. Regime Shift and the Post-Crisis World of Mortgage Loss Severities, Federal Reserve Bank of Philadelphia Working Papers, 17-08.
[235] An, X. and L. Cordell. 2019. Mortgage Loss Severities: What Keeps Them So High? Federal Reserve Bank of Philadelphia Working Papers, 19-19.
[236] For example, in 2013, the CFPB finalized a rule imposing more restrictions on servicers during the delinquency and foreclosure process. See https://www.federalregister.gov/documents/2013/02/14/2013-01248/mortgage-servicing-rules-under-the-real-estate-settlement-procedures-act-regulation-x.
[237] Cordell, L. and L. Lambie-Hanson. 2016. A Cost-Benefit Analysis of Judicial Foreclosure Delay and a Preliminary Look at New Mortgage Servicing Rules. Journal of Economics and Business 84: 30–49.

Support for Model Structure

Two-Stage Structure

As described above, the First Lien LGD model uses a two-stage approach, where the first stage assigns the projected length of elapsed time between default and liquidation, and the second stage projects the loss severity given this timeline.

The two-stage structure serves multiple benefits. First, it accounts for the fact that LGD is most sensitive to the macroeconomic environment as of the liquidation date, as the sale price of the property is determined based on the home value at the time of the sale. Calculating the timeline in the first stage allows for the identification of the liquidation date used in the second stage (Loss Severity Model). Next, it allows for a simple method of differentiating credit losses in the LGD model and OREO losses in the PPNR model. By allocating losses based on the portion of the timeline assigned to OREO, the model avoids the need to directly model the complicated dynamics of the transition from default to REO to disposition.

Lastly, the two-stage structure provides flexibility in case that liquidation timelines were to change or that it became appropriate to project separate timelines for different loans in the future. A further discussion on the factors that can affect liquidation timeline can be found below and in C.ii.b.(4).

Timeline Model

The Timeline Model assigns a projected liquidation timeline of 22 months to all loans. The decision to assign a single timeline projection to all loans is based on the principle of simplicity, and analysis that showed that more complex modeling approaches have limited improvements to model sensitivity. See Section C.ii.b.(4) for more discussion of these more complex modeling approaches. Given the limited improvements in model performance and largely stable projections when applying a single timeline for all loans, the Board adopted a simple, more interpretable approach.

Given the choice of a single projected timeline, the calibration of this projected timeline of 22 months is based on an analysis of liquidations in the First Lien PD Data that occurred between January 2005 and December 2019. A start date of January 2005 was chosen to ensure coverage starting before the housing market decline of the 2008 financial crisis period, while an end date of December 2019 was used to avoid impacting the projections with data from during the COVID-19 pandemic period. Due to foreclosure moratoria and generous forbearance programs during this period, liquidation timelines swelled, as lenders were unable to complete the liquidation process without the ability to foreclose. This unique environment is not reflective of the behavior the Board expects in the housing market during a future prolonged housing market downturn.

While including pandemic-era data would expand estimated liquidation timelines, the Board tested using longer and shorter sample periods prior to the pandemic and determined that the estimate of 22 months is unaffected. This is reasonable, as the vast majority of liquidations occurred during the 2008 financial crisis period.

With the sample determined, the Timeline Model is calibrated to match the 75th percentile value of historic liquidation timelines in the sample. The 75th percentile value is chosen compared to other points in the distribution, such as the mean or the 90th percentile. The Board selected the 75th percentile for a handful of reasons. Compared to the mean, applying the 75th percentile value is consistent with the stress testing principle of conservatism. Based on the Board's experience and expertise, a conservative value is warranted. In particular, per An and Cordell (2017), there is reason to believe liquidation timelines extend during periods of housing market stress, as a large number of defaults at once can overwhelm the legal foreclosure infrastructure. Additionally, the 75th percentile value reflects that due to regime shifts in the mortgage market (see An and Cordell, 2019), liquidation timelines have lengthened in the aftermath of the 2008 financial crisis.

Choosing a higher percentile, such as the 90th percentile, would be even more conservative; however, Board analysis of historical PLS and GSE data indicated that using a higher percentile would lead to projections of LGD that are well above historical levels for many loans, even during periods of stress. The Board also compared loss rates estimates using the 75th percentile to loss rates assigning liquidation timeline based on an alternative, more complex approach (described in more detail in C.2.b.(4)), and determined that the loss rates under the alternative approach were close to those projected using the 75th percentile historical liquidation timeline. This provides additional support that the Board's approach produces reasonable projections.

Therefore, in line with the stress testing principles of conservatism and focus on the ability to evaluate the impact of severe economic stress and because the projected loss rates produced using the 75th percentile are reasonable, liquidation timeline is calibrated based on the 75th percentile historical value.

Loss Severity Model

The Loss Severity Model uses a weighted least squares regression approach to project the share of the balance of the loan that will not be recovered by the lender, based on the timeline projection as well as other variables. A weighted least squares approach is a form of a linear regression model, a simple modeling approach that produces reasonable, accurate projections of an outcome variable (in this case, loss severity). Weights are applied, as described in Section

C.ii.b.(1), to produce an estimation sample that is representative of the FR Y-14M portfolio loans for which it is used to project losses. The model uses linear regressions due to their simplicity and popularity in academic literature, as discussed, the review of literature above. While certain research relies on more advanced modeling techniques to bound LGD estimates between zero and one and account for the shape of the distribution of actual LGD, the Board determined that the added complexity was not justified by the amount of improvement in model performance.[238]

Next, the Board models separate equations for three credit classes: Prime, Alt-A, and Subprime loans.[239] These categorizations were determined algorithmically to align as closely as possible with the reported credit class in the PLS data, while keeping the definition simple. Using the algorithmic, rather than directly reported, definition ensures consistent treatment of loans across firms and reporters in the sample. Previous work, such as Pennington-Cross (2003), underscores that different classes of loans behave substantially differently. Analysis of historical PLS and GSE data confirm that loans characterized as Subprime have consistently higher loss severities than Alt-A or (especially) Prime loans, even accounting for other observable factors. Modeling these separate equations can allow the model to accurately project both the extremely high loss severities observed during the 2008 financial crisis as well as the relatively low loss severities observed in recent years. It also ensures that the improved underwriting of mortgages observed following the 2008 financial crisis period is appropriately accounted for in the model.

[238] Additionally, while loss severity tends to be between 0 and 1, it is theoretically possible for loss severity to be less than 0 (if the lender gets a more-than-full recovery on the property sale) or greater than 1 (for instance, if the costs of disposition of the property are greater than the proceeds of any sale). Given this, artificially binding loss severities at 0 and 1 may lead to inaccurate results for some loans.
[239] As defined in Table C5.

Support for Variables and Transformations included in the Loss Severity Model

This section focuses on the Loss Severity Model, given the structure of the Loss Severity Model as a regression model with many covariates. The overall strategy for determining the appropriate variables and transformations in the model is similar to that of the PD model; a wide range of variables were considered, while final variable selections were made based on economic support, statistical fit, simplicity, and conservatism. Included loan and borrower characteristics were limited to those available in both the PLS and the GSE data. Unlike the PD model, however, the variables are chosen simultaneously for all equations in the Loss Severity Model. This is reflective of the expectation that while the different credit classes behave differently, the same factors are associated with higher or lower loss severity across different credit classes. The simultaneous variable choice also simplifies the interpretability of the modeling approach.

Given these factors, the variables included in the model are described below:

- Property type (condo, multi-unit, planned unit development;[240] single-family properties serve as the base case): Compared to single family houses, other property types may have different expected recovery values due to differences in the potential resale market. Across all credit classes, the following trends are observed in the data, based on the coefficients on these variables:
  - Multi-unit buildings have higher loss severity compared to single family houses.
  - Planned unit developments have lower loss severity compared to single family properties.
  - Condos have higher loss severity among Prime and Alt-A loans; for subprime loans, condos have lower loss severities.
- Origination credit score: In general, borrower characteristics such as credit score impact LGD less than PD. Nevertheless, a slight decrease in LGD is observed for borrowers with credit scores above 720, based on the coefficients on these variables. Since the construction of the definition of Subprime in the LGD model does not allow for Subprime borrowers to have credit scores above 720, this variable is not included in the Subprime equation.
- Judicial foreclosure state indicator: Because of the additional costs of judicial foreclosure, loss severity is higher for loans in judicial states. However, as previously discussed, the Board treats loans similarly across different states, to avoid unduly penalizing loans

[240] A planned unit development is a group of properties where all homeowners belong to a homeowners association. The instructions for FR Y-14M, Schedule A.1 direct reporters to report loans as "planned unit development" only if it is known that the property is in a planned unit development but there is no information on the underlying property type.

based on the state of the property. Therefore, to project LGD, this variable is assigned a single value, calibrated based on the share of loan balance reported on FR Y-14M, Schedule A (First Lien) in the period immediately prior to the start of the projection period.

- Origination LTV: Even when accounting for updated LTV, origination LTV is still predictive of LGD. The model categorizes loans into low LTV (less than or equal to 65 percent), medium LTV (between 65 and 80 percent), and high LTV (greater than 80 percent) buckets. Lower LTV loans have lower loss severity, as observed in the coefficients on this variable, reflecting the larger equity cushion provided by the borrower.
- Updated LTV at liquidation: This measures the equity position of the property at the time of liquidation. Specifically, updated LTV is calculated based on the origination LTV, the share of the original loan amount that remains unpaid (unpaid principal balance),[241] and the change in the house price index in the county[242] (or state, if county is unavailable) from the quarter of origination through the quarter of liquidation (based on the projected quarter of default and the projected timeline). The Board performed sensitivity analysis of the model to changes in different variables, which showed that the updated LTV of the loan at liquidation is critical in determining how much of the loan balance can be offset by the sale of the property.
- Change in HPI over previous year as of liquidation: This variable enters with a negative coefficient, reflecting that loss severities are higher when the property is sold into a declining housing market.
- Indicator for liquidations occurring after September 2010: Following allegations of unfair foreclosure procedures that emerged in 2010,[243] lenders generally increased compliance efforts related to foreclosure procedures, increasing foreclosure costs. This, as well as additional changes in the housing market that increased servicer obligations during foreclosure, increased loss severity. To account for these housing market changes, an indicator variable is used to identify liquidations occurring after September 2010. This coefficient, which is positive—in line with expectations—is applied to all loans liquidating during the supervisory stress test projection period.
- Loan purpose (rate/term refinance, cash-out refinance; purchases serve as the base case): Loans that were originated as refinances (as opposed to purchase mortgages) have higher loss severity, based on the coefficients on these variables. This finding is consistent with Agarwal, Ben-David and Yao (2017),[244] and could be reflective of appraisal bias. Loss severity is especially high for cash-out refinances, when equity is extracted from the property at origination.

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[241] Because the First Lien LGD Model accounts for the change in loan balance from origination when defining updated LTV, the definition is slightly different compared to the PD model. This is reasonable as the borrower's equity (or lack thereof) is even more fundamental to the recovery on the loan than it is to the probability of default. In particular, a higher share of paid-down balance means that a smaller amount of the original loan balance must be repaid to the lender to avoid losses on the loan.

[242] Similar to the PD model, the county of a property is assigned based on the reported zip code in the FR Y-14M report.

[243] *See* https://www.theguardian.com/business/2010/oct/14/wells-fargo-mortgage-foreclosure-robo-signer.

[244] Agarwal, Sumit, Itzhak Ben-David, and Vincent Yao. "Collateral Valuation and Borrower Financial Constraints: Evidence from the Residential Real Estate Market," *Management Science* 61, no. 9 (2015): 2220–40, http://www.jstor.org/stable/24551594.

- Occupancy type (secondary residence, investment property; loans for primary residences serve as the base case): Both second homes[245] and investment properties have historically higher loss severity than primary residences, based on the positive coefficients on these variables.
- Loan size: Loss severity is associated with loan size historically based on analysis of the GSE and PLS data, but the impact varies at different loan sizes. Broadly, loss severity tends to decline as loan size increases until the loan amount reaches approximately $600k. Below this amount —especially for very small (less than $100k) loans—smaller loans tend to have higher loss severities. This could reflect lenders taking less effort to maximize the recovery value on smaller loans. Above $600k, the trend reverses, with larger loans having slightly larger loss severities. This reflects that properties secured by larger loans are less liquid than other houses, reducing the recovery value under stress. Splines are used to account for these changing effects; the findings above are consistent with the coefficient estimates on these variables.
- Liquidation timeline: This variable is set to 25 months in the loss severity model. As described in Section C.ii.b.(1), the time between default and liquidation is assumed to equal 22 months for all loans. Because the liquidation timeline in the loss severity model is defined as the period between a loan reaching 90 days past due and liquidation, an additional three months are added to the 22 month period. As previously described, liquidation timelines are a key driver of loss severities. Longer liquidation timelines are associated with higher expenses such as taxes, insurance, and property maintenance. The impact of liquidation timelines on loss severity is non-linear, as demonstrated by the coefficients on these variables, reflecting that after approximately two years the impact of an additional month on loss severity is reduced. However, given the assumption that the liquidation timeline is the same for all loans, this non-linearity is used merely to calibrate the model parameters and does not impact loss severity in practice.
- Origination year: Indicator variables are used to account for increased LGD observed in historical PLS and GSE data for 2006 and 2007 originations. During this period, there were widespread, unobserved underwriting effects that impacted loss severity.

Additionally, since the model relies on two separate data sources for calibrating the Loss Severity Model, an indicator variable is used to identify liquidations in the GSE (as opposed to the PLS) data. The model estimates show that given equivalent characteristics, loans in the PLS data have higher loss severities (about 5 percentage points higher for prime loans, and between 8 and 9 percentage points higher for alt-A and subprime loans) than loans in the GSE data. However, it is not clear whether the portfolio loans for which the First Lien Model projects

[245] In this context, second home refers to a residence of the borrower that is not the primary residence.

losses will behave more similarly to the loans in the PLS data or the loans in the GSE data upon default. Because of this uncertainty, and consistent with the stress testing principle of conservatism, the Board treats all loans as PLS, rather than GSE, loans when projecting LGD.

Support for Data Used to Estimate LGD Model Parameters

The data used to calibrate the Timeline Model is the same dataset used for the First Lien PD model. As described with respect to the First Lien PD model, the First Lien PD Data used to calibrate the Timeline Model is comprised of portfolio loans that have comparable characteristics to loans reported on FR Y-14M, Schedule A (First Lien). Unlike the FR Y-14M report, the First Lien PD Data include performance history in the years leading up to and during the 2008 financial crisis period, a period of significant housing stress with lots of defaulted loans. To ensure coverage of this period, the First Lien PD Data is used to calibrate estimates of timelines.

The First Lien Loss Severity Model uses the PLS and GSE data. These data sources are used due to their robust coverage of gross loss and recovery information. While both the First Lien PD Data and FR Y-14M data include fields to report losses, the coverage of these fields in the historical data is sparse. One concern about using data from loans included in securities, as opposed to loans on bank portfolios, is that LGD on portfolio loans may be systematically different than LGD on loans included in mortgage-backed securities. For instance, if servicers have a larger incentive to maximize the recovery for loans on their own balance sheet, compared to loans they are servicing for other owners, this may lead to lower LGDs on portfolio loans. Despite this concern, the Board uses these data sources due to the large data size and lengthy time period covered by the data, which is not available from other sources. To ensure LGD estimates are reasonable, the Board regularly monitors the performance of the model, including by comparing projections from the LGD model to benchmark models. This monitoring indicates that the model calibrated on PLS and GSE data produces reasonable estimates of LGD, suggesting that these data sources are reasonable for use in the supervisory stress test model, and appropriate given their coverage of different historical periods, including the 2008 financial crisis.

Support for Allocation of Losses Between Credit and OREO Losses

The First Lien Loss Model assigns eight months of the liquidation timeline to the REO stage and allocates OREO losses to be accounted in the PPNR model based on the share of the liquidation timeline that consists of this REO stage. This section describes support for this implementation in the supervisory stress test.

The assumption that the REO stage accounts for eight months of the liquidation timeline is drawn from estimates from Cordell et al. (2015).[246] The assumption that losses can be allocated based on the share of the timeline during which the loan is in the REO stage is a simple implementation that allows losses to be allocated reasonably. Without a simple assumption, the model would need to separately estimate the transition of a loan from default to REO to liquidation, substantially increasing the model complexity for a comparatively small increase in precision.

Additionally, while the model causes all credit losses to be realized, regardless of when the loan is liquidated, OREO losses are only incorporated when the REO timeline is projected to overlap with the nine-quarter projection horizon. This differentiation accounts for the differences in the accounting of credit losses and PPNR. While credit losses are charged off and deducted from a firm's allowance at the time of default, changes to the valuation of real estate

[246] Cordell, L., L. Geng, L. Goodman, and L. Yang. 2015. The Cost of Foreclosure Delay. Real Estate Economics 43(4): 916–956. The average REO timeline reported is seven months; however, this includes data from just prior to the end of the sample, which could be affected by the impacts of censored loans. Therefore, eight months is assumed.

owned by the bank are applied in the quarter of the change. Therefore, accounting for OREO expenses that are incurred outside of the nine-quarter horizon would not be appropriate.

(3) Adjustments and Data Cleaning Steps

Timeline Model Sampling and Cleaning

As described in Section C.ii.b.(1), the Timeline Model is calibrated based on liquidations observed in the First Lien PD Data from 2005 through 2019. To ensure representativeness, only portfolio loans (as defined in Section C.ii.a.(3)) are included. Additionally, all loans with government guarantees (such as FHA or VA loans) are removed, given that losses are not projected on these loans in the stress test. In particular, while Ginnie Mae loans return to a firm's balance sheet when they become delinquent, these loans retain their guarantee and would not be treated like other portfolio loans. Therefore, these loans are excluded.

Additional filters are included for reasonableness; notably, loans are excluded if the first observation of the loan shows it as in foreclosure, REO, or liquidated.

With the sample created, the timeline is calculated as the number of months that elapsed between the loan reaching 180 or more days past due and the loan liquidating. To avoid outliers and potentially problematic data, loans with calculated timelines greater than five years (60 months) are removed. While timelines of five years appear long, Cordell et al. (2015) notes that in the aftermath of the 2008 financial crisis, timelines extended significantly, especially in judicial states. Still, the Board determined based on review of the First Lien PD Data that timelines extending beyond 60 months are rare and likely reflect outliers or data errors. Because the Board applies the 75^{th} percentile timeline to all loans, the impact of excluding these outliers is small; however, excluding outliers prevents the timeline projection from being overly conservative.

From this final dataset, the distribution of projected timelines is observed. As described previously, the supervisory stress test applies the timeline associated with the 75th percentile value of historically observed timelines.

Loss Severity Model Sampling and Cleaning

The Loss Severity Model is estimated using loans in the PLS and GSE data that were originated between 1999 and 2013 and liquidated prior to September 2015. While this sample excludes liquidations after 2015, as the majority of liquidations in the sample were observed during and immediately following the 2008 financial crisis period, the impact of the sample end date on projected LGD is small, as a small percentage (less than 15 percent) of the total liquidations observed in the data have occurred since 2015. The Board tested using more recent data to estimate the LGD model parameters and determined that the impacts on projections were small, given the limited number of additional liquidations that are added. See Section C.iii.a for further discussion of this issue.

Certain filters are applied to this starting dataset. These filters are applied based on the Board's experience and expertise. Due to the nuances of the individual input datasets, the exact filtering process is developed and performed separately for the two datasets. In particular, the Board reviewed each dataset separately and, in some cases, identified data trends that justified adding filters. In some, but not all cases, these data trends were observed in both datasets; the Board applied filters to each dataset only when the data trends in that dataset justified these filters.

In the GSE data, loans with missing or invalid values for key fields used in modeling—including the proceeds from the sale of the property, original LTV, credit score at origination, or occupancy type—are removed, as are loans where the liquidation is reported in the same year or a previous year from the origination year. Additionally, loans that were repurchased out of the pool were removed, as repurchases often reflect fraudulent or otherwise problematic origination practices. Loss severity is calculated as described in Section C.ii.b.(1). The distribution of realized loss severities in the historical data can be wide; however, extreme outliers, with actual LGD less than -50 percent or greater than 150 percent are removed to avoid the model being impacted by outlier values.[247] As discussed in Section C.ii.b.(1), while it is plausible for LGDs to be less than zero or greater than one in some cases, values far outside of this range are unlikely, and may reflect data errors or outliers. Meanwhile, the linear regression model approach is sensitive to extreme outliers; therefore, setting a threshold is important to avoid unintended impacts to model parameters. Additionally, loans with exactly zero loss severity are removed; despite the removal of mortgage insurance recoveries in the definition of loss severity, the GSE data still showed a much higher rate of loans with exactly zero reported losses compared to the PLS data. This raised concerns that losses of exactly zero could be indicative of missing or erroneous data; as a result, loans with zero losses are removed from the GSE data.

In the PLS data, loans are included if they are observed in foreclosure or REO at some point in their history, or if the reported loss amount is greater than zero. Only loans that were originated for purchase or refinance are included, consistent with the PD sample. Loans with invalid or extreme original LTV ratios (less than or equal to 0, or greater than 135) are removed, as are loans that paid off while current or paid off while delinquent with no loss. Next, loans with missing property type—as well as manufactured housing—are removed, as these loans

[247] The Board includes historical loans in the data used to estimate the model coefficients with actual LGD as low as -50 percent; however, as described in Section C.ii.b.(1), when projecting LGD, the Board sets a floor of zero to the LGD projections. This treatment allows the model to reflect different historical behavior of loans, while assuming, in line with the stress testing principle of conservatism, that firms will not accrue negative losses on any defaulted loans in the supervisory stress test.

cannot be mapped to the property categories in the model.[248] Loans with private mortgage insurance—which are rare in the PLS sample—are also removed to avoid incorporating mortgage insurance recoveries into loss severity estimates.[249] Loans that are not first liens are removed, as losses on junior liens are modeled by the Home Equity Model,[250] and loss severity for junior liens is fundamentally different than that of first liens. Finally, extreme loss severity values are filtered out, similar to the GSE data.

A few additional data treatments are applied for representativeness. Credit class is defined consistently with the description in this section. However, in the PLS data, negatively amortizing loans are treated as Alt-A, regardless of other features, based on the Board's experience and expertise and consistent with the historical experience that negative amortizing features were often included in Alt-A loans.[251] Loans in the PLS sample that are not reported as "Prime" in the deal documents, but meet the criteria to be treated as Prime loans, are removed from the sample, to avoid biasing the results for Prime loans.

House price data are merged at the county level, at different time periods. To calculate updated LTV at liquidation, as well as year-over-year change in house prices, house price index is merged as of the month of origination and the month of liquidation. When county-level house price index is available, it is used with property county assigned based on the reported property

[248] Less than 1 percent of liquidated loans in the PLS data are manufactured housing.
[249] Unlike in the GSE data, in the PLS data it is challenging to disaggregate recoveries into different sources.
[250] *See* the Home Equity Model Description.
[251] *See* Woodward and Raju 2008. "The second reason that Alt-A loans were so popular was because many programmes offered teaser rates for speculators. These loans, known as adjustable-rate mortgages, have initial negative amortization to keep monthly payments low."
Woodword, L. and S. Raju, 2008. The Implosion of the Alt-A Mortgage-Backed Securities Market. Journal of Risk Management in Financial Institutions, 2(2): 214-225.

ZIP code;[252] loans that cannot be assigned a county house price index value based on the reported property ZIP code are excluded from the sample used to estimate the coefficients.

Servicer Advances in the PLS Data

When cleaning the PLS data for use in estimating the LGD model parameters, the Board considers that in the PLS data, unlike for most of the portfolio loans for which losses are projected in the supervisory stress test, the servicer of the loan does not own the loan. Therefore, the PLS data incorporates servicer advances, which are not relevant for portfolio loans. As background, for private label securities, servicers often continue to pay interest on delinquent loans using their own funds, until the servicer determines that advances are not recoverable.

To ensure the loss severities observed in the PLS data are representative of losses on portfolio loans, the Board removes servicer advances of interest payments from the losses reported in the PLS data. This adjustment is not necessary in the GSE data, as loss severity in the GSE data can be directly calculated based on the underlying sources of losses and recoveries, as described previously in Section C.ii.b.(1), and thus does not include any amounts advanced from the servicer.

While conceptually, reversing servicer advances is straightforward, in practice it requires a series of complex adjustments. The process is summarized and then explained in more detail below. First, the model calculates the servicer advance rate, or the share of months a loan is delinquent that the servicer advanced payments. While the servicer advance rate can be directly observed for amortizing loans,[253] for non-amortizing loans, the Board imputes the rate by

[252] Because only the 3-digit zip code is reported in the GSE data, the model maps these 3-digit zip codes, rather than 5-digit zip codes, to counties. Because 3-digit zip codes cover a larger area than 5-digit zip codes, this makes the mapping less precise than if 5-digit zip codes were used. Nevertheless, the 3-digit zip codes allow for enough variation by geography to account for differences in regional historical house prices.

[253] In particular, the Board assumes that advance has been made when the amount owed from the loan to the investors of the private label security decreases in a month while the loan is delinquent.

identifying a comparable amortizing loan, and then adjusts that rate down by using another third-party dataset to calibrate the ratio of servicer advances on non-amortizing loans relative to that of similar amortizing loans.[254] Having determined the servicer advance rate for each PLS loan, and using the number of months of delinquency and the monthly interest due, the Board computes the interest advanced for each loan. Finally, this servicer advance amount is subtracted from the losses reported for that loan in the PLS data.

This process for removing servicer advances produces loss severity in the PLS data that is comparable to the LGD that is applied by the First Lien LGD Model.

Projection Data Cleaning in LGD

The LGD model is applied to all loans for which PD is projected in the supervisory stress test. No additional data cleaning is required for application in the LGD model. The first lien mortgage data reported by covered institutions on FR Y-14M, Schedule A (First Lien) is merged with historical house price index—taken from the historical data used to build the Supervisory Stress Test Scenarios[255]—as of the origination quarter and projected historical house price index from the Supervisory Stress Test Scenarios as of the projected liquidation quarter. As in the PD model, the ZIP codes reported in the FR Y-14M report are mapped to counties and house prices are merged at the county level, or the state level, if house price index is not available for that county. As described previously, in the scenario, house price index is expected to fall by the same percentage in each geography as the percentage decline in the national scenario. This methodology allows the Board to apply macroeconomic variables at the regional level. For more

[254] Determined by initial delinquency date, liquidation date, and credit class.
[255] *See* Section III.B of the Enhanced Transparency and Public Accountability Proposal for additional information on data cleaning of the historical house price index data in the scenario dataset.

information, see Section III.B of the Enhanced Transparency and Public Accountability Proposed Rule.

Because of the elapsed time between default and liquidation, many loans are projected to liquidate outside of the 13-quarter horizon over which supervisory stress test scenarios are produced. To account for these loans, it is necessary to make assumptions about house price appreciation after the end of the scenario. The Board considered making a simple assumption that house prices would remain frozen indefinitely at the level designated in the 13th quarter of the stress test scenario until all loans liquidate. This approach would be simple and avoid the need to make projections about the path of house prices years after the start of the projection period. However, this flat house price assumption is unreasonably conservative, as house prices are usually increasing in benign periods. Therefore, the Board assumes a constant 1 percent annual house price appreciation for all quarters after the 13th projection quarter. This modest projected growth is still in line with the stress testing principle of conservatism, as historically, house price appreciation tends to exceed 1 percent during benign periods. Despite this, this assumption allows for some amount of growth, in line with historical expectations. Because this only applies to loans liquidating outside of the 13-quarter scenario period, the impact of this assumption is limited.

(4) Alternatives

Alternative Model Structures

Two-Stage Model Structure

As previously described, the First Lien LGD Model calculates LGD in two stages, where the first stage projects the elapsed time between default and liquidation and the second stage projects the share of the loan balance at default that is unable to be recovered based on this timeline.

One alternative approach is to simplify the model to a single stage, where loss severity is calculated directly without a separate Timeline Model. Because the same projected timeline is assigned for all loans, it could be beneficial to model LGD in a single stage, avoiding the need to project timeline and potentially introducing additional errors or imprecision into the calculation. While a single-stage model has the benefit of additional simplicity, the Board uses the two-stage, for a few reasons. First, the assignment of a timeline allows for the allocation of losses between credit losses and REO, which otherwise would need to be modeled separately. Second, it accounts for the fact that LGD is most driven by the LTV ratio as of the liquidation date, rather than as of the default date; this may vary substantially based on where in the scenario the default occurs. Finally, the two-stage approach allows the Board to flexibly alter the assumptions surrounding projected timelines if they change over time. For these reasons, the two-stage approach is preferred over a single-stage LGD model.

Another alternative approach is to model the projected recovery value directly, rather than model the share of the loan balance that will not be recovered. An example of this approach can be found in the supervisory stress test Commercial Real Estate LGD Model,[256] which projects the property value at the time of default, and then applies a haircut to reflect that distressed assets tend to sell at a discount. This approach has the benefit of being simple, easily interpretable, and not reliant on many additional loan and borrower characteristics. However, a drawback of this approach is that there is less academic work related to first lien mortgages to draw on in developing this model structure; conversely, LGD models using linear regression

[256] *See* Section B.ii.b in the Commercial Real Estate Model Description.

approaches are common in the public domain and are therefore better understood. Relying on a more commonly used approach allows the Board to draw on other sources in developing the First Lien LGD Model.

Timeline Model Alternatives

The Timeline Model projects a single timeline for all defaulting loans, calibrated to 22 months based on historical data. This is a relatively simple approach. Alternative approaches allow the model to differentiate projected timelines based on loan, borrower, and macroeconomic characteristics.

Empirically, the most important driver of liquidation timelines is the state foreclosure regime. An alternative approach would be to assign one projected timeline for loans in judicial states, and a separate, shorter timeline for loans in non-judicial states. However, including foreclosure regime type in the model could lead to differential treatment of loans based on the property state. Furthermore, state foreclosure regimes are subject to change, and in certain cases states cannot be easily categorized as judicial or non-judicial states.[257]

Additionally, the Board has tested using a regression model to project liquidation timeline, based on loan, borrower, and macroeconomic characteristics. These characteristics include state foreclosure type—as discussed in the previous paragraph—as well as other variables, such as credit score, loan amount, and various macroeconomic variables. This alternative provides projections of liquidation timelines that are calibrated specifically for each loan in each quarter. However, the Board determined that the benefits of this model do not outweigh the costs. First, while some of these variables are statistically significant, the variation

[257] For instance, certain states formally have non-judicial foreclosure available, but in practice lenders rely on judicial processes for foreclosure regardless. Additionally, it is possible for states to shift from judicial to non-judicial regimes (or vice versa) over time; incorporating this shift would require additional complexity in the model.

in actual liquidation timelines explained by these variables is small, as liquidation timelines of individual loans are often longer or shorter for idiosyncratic reasons. Second, an additional challenge with using a regression model is the problem of censorship. Censorship occurs when only certain loans can be fully tracked prior to the end of the sample. In this case, the issue occurs when considering loans that defaulted prior to the end of the sample period, but have not yet liquidated. For these loans, the timeline cannot be precisely computed; while it is known that the timeline will not be less than the number of months elapsed between the default date and the end of the sample, it is not known how many additional months will elapse following the end of the sample. If these loans are not considered, loans that defaulted close to the end of the sample will be included only if they liquidate quickly, biasing timeline estimates downward. This censorship can be accounted for using statistical techniques; however, these techniques can introduce noise and possible errors. Furthermore, the other loan, borrower, and macroeconomic characteristics were not shown to substantially impact timeline projections in practice, as liquidation timelines are somewhat idiosyncratic. Given the statistical complications of treating censored loans and the limited improvements to predicted timelines when calibrated with a regression model, the Board does not use a regression model approach for projecting first lien liquidation timelines.

Loss Severity Model Alternatives

The Loss Severity Model uses a weighted least squares approach, a form of a linear regression, to project loss severity for first lien mortgages. As described in the review of literature in Section C.ii.b.(2), there are examples in academic work of other model structures that use other statistical methods to account for certain features of the LGD distribution that linear structures do not handle optimally. Despite these considerations, the linear regression approach is chosen for its simplicity and interpretability; in practice, the reasonableness of the model projections suggest that the application of a linear model is appropriate.

Given the choice of a linear model, the Board considered alternative methods of defining credit classes to be modeled separately. Three equations, corresponding to Prime, Alt-A, and Subprime, are estimated due to the significant differences in historical behavior across these categories. The Board also considered estimating two equations, Prime and non-Prime (combining Alt-A and Subprime); however, ultimately, differentiating Alt-A and Subprime loans notably improved the model's explanatory power. In addition to the number of categories, the Board also considered alternatives to the definitions used to assign loans to these credit classes. As described in Section C.ii.b.(1), the LGD model assigns credit class based on observable loan characteristics, such as original LTV, origination credit score, and documentation type. However, the PLS data directly report loans into these categories in a separate field, and credit class is also directly reported in the FR Y-14M data. There is no credit class reported in the GSE data. While such loans could be treated as Prime loans, given the relatively strict underwriting criteria for loans sold to GSEs, it is not clear that this definition would be analogous to the definitions used in the PLS or FR Y-14M data. This alternative definition would rely on directly reported—rather than imputed—information and reflect that underwriting criteria may have improved over time, even considering the observable characteristics of the loan. Despite the advantage, the Board relies on the credit class definitions based on observable loan characteristics. Using these definitions ensures consistency between the definition of credit classes between the data used to estimate the model parameters and the data used to project losses. It also ensures that differences in credit classes are not driven by the subjective determination of individual servicers.

Alternative Variables and Transformations in the Loss Severity Model

This section focuses on the Loss Severity Model, given the structure of the Loss Severity Model as a regression model with many covariates.

The Loss Severity Model considers a wide range of variables that are associated with LGD. Ultimately, the most important factor in determining the recovery on a first lien mortgage is the updated LTV at the time of liquidation; while other loan and borrower characteristics can be impactful, the loss severity calculation is less sensitive to these factors than is the probability of default calculation.

In some cases, where variables are determined to be important, but the relationship is less consistent than that of the PD relationship, continuous variables are collected into categories in the specification. This is the case in the Loss Severity Model for both original LTV (grouped into loans with less than a 65 percent LTV ratio, 65-80 percent LTV ratio, and greater than 80 percent LTV ratio) and credit score at origination (split into loans to borrowers with a score of less than 720 or above 720). An alternative approach is to include these terms directly in the model and allow projected loss severity to smoothly increase or decrease as the value of these variables change. However, the Board determined that for these variables, the impact concentrated at the points in the distribution where the categories are defined, rather than smoothly across the entire range of values. In particular, LGD is categorically higher for high LTV loans (with LTV above 80 percent at origination) and categorically lower for low LTV loans (with LTV of 65 percent or below at origination). Meanwhile, credit score has a minimal impact on loss severity altogether; if not aggregated into large categories, the impact would be unobservable. The model includes a flag for whether the credit score is above 720 to account for the small differences observed in loans to high credit score borrowers.

In addition to the variables included in the model, an additional factor that is relevant in determining the loss severity of a first lien mortgage is the liquidation type. First lien mortgages can liquidate in a variety of ways, including but not limited to the following:

- REO: REO liquidations operate as described in the First Lien LGD Model structure. A defaulted loan goes through foreclosure proceedings, and the property becomes owned by the lender. The lender usually sells the property to maximize the recovery.
- Foreclosure sale: Foreclosure sales occur when a property in foreclosure is sold at an auction.
- Short sale: Short sales occur when the borrower sells the property for less than the value of the loan, leading to a loss for the lender.
- Charge off: In some cases, the lender may choose not to enter foreclosure proceedings, and instead pursue recovery through other means, or write the balance off entirely.

In general, REO liquidations have higher LGD than other liquidation types, as the process of foreclosing on and maintaining a property is more costly than an earlier disposition. Including a term to identify REO liquidations therefore adds explanatory power to the model. Despite this, it is not feasible to consider liquidation type in the context of the supervisory stress test, as the model cannot project how a given loan will liquidate in the case of default. Including the liquidation type would require developing an additional model to determine the likelihood of the loan liquidating via REO rather than other means, which would introduce additional potential for error and complexity into the model. Given this roadblock, liquidation type is not incorporated into the Loss Severity Model.

Alternative Definitions of Loss in the First Lien Model

The Board incorporated multiple considerations in determining how to calculate the losses on a given loan. Ultimately, the model calculates LGD as the recovery rate subtracted from one, where the recovery rate is the share of the loan balance that is recovered at liquidation, net of costs of liquidation, with the caveats that costs associated with servicer advances are reversed and any recovery associated with private mortgage insurance payouts is ignored.

The Board ignores any recoveries associated with private mortgage insurance payouts in line with the principle of conservatism. While mortgage insurance is required for loans that meet certain criteria and are sold to GSEs, the share of portfolio loan balance reported on FR Y-14M, Schedule A (First Lien) with mortgage insurance is less than 2 percent. Because of the differences across loan populations in the prevalence of mortgage insurance, mortgage insurance recoveries are excluded from the definition of loss used in the model. In particular, if the model is calibrated on a subset of loans that are more likely to have mortgage insurance than the loans contained in the FR Y-14M data, the model could understate LGD projections in the supervisory stress test. An alternative methodology is to subtract projected mortgage insurance recoveries from the projected loss balance after the equations are applied to a loan. However, given the limited share of FR Y-14M loans that have mortgage insurance, the benefits of including mortgage insurance recoveries in the LGD model do not outweigh the additional complexity of accounting for them. Additionally, unlike with loans that are guaranteed by government agencies, such as FHA and VA loans, mortgage insurance is provided by private companies that could face challenges paying out insurance claims—particularly during a period where many mortgages default and liquidate in a short period of time. Excluding mortgage insurance recoveries conservatively accounts for the possibility that the mortgage insurance provider (or counterparty) will default on its obligations.

Next, the Board considered the impact of including additional sources of losses in addition to the remaining unpaid principal balance on a loan. In particular, these additional sources are accrued but unpaid interest and carrying costs associated with the elapsed time between default and liquidation. Accrued interest refers to interest charges that are accrued but unpaid, which can be capitalized into loan balance at the time of default. After the borrower becomes delinquent, lenders may move the loan to "non-accrual" status and stop applying interest to the loan; however, there is an interim period during which interest is charged on a loan and unpaid. Carrying costs refer to the implicit costs to the firm that arise from the delay between when the loan defaults and when the proceeds of the sale of the property are provided to the firm. This is potentially costly to the firm as the present value of the recovery may be lower if it is not received until a long time after the loan has defaulted. Because foreclosure and liquidation can take significant time for mortgages, these costs could theoretically be significant. However, the Board determined that both accrued interest and carrying costs may already be captured by the PPNR model. Therefore, to avoid the potential for double-counting losses associated with accrued interest or carrying costs, the Board excludes accrued interest and carrying costs from first lien losses.

(5) Questions

Question C5: The Board is seeking comment on whether to use a model that projects the recovery value of the collateral instead of directly projecting the share of the loss that the lender will not be able to recover.

Question C6: The Board uses a simple assumption to assign a single liquidation timeline to all loans, regardless of loan, borrower, or macroeconomic characteristics. The Board is seeking comment on whether to continue that approach, as opposed to a more complex model. Furthermore, the Board seeks comment on how to assign timelines for mortgages in different states, given the differences in practices across U.S. states.

Question C7: The Board is seeking comment on whether it is appropriate to incorporate measures of accrued interest and carrying costs into total losses when projecting First Lien LGD.

Question C8: Should the Board consider changing the assumption that house prices will appreciate at a constant one percent annualized rate after the end of the 13-quarter projection horizon? If so, how should the Board project house price changes for loans that liquidate after the end of the 13-quarter projection horizon.

c. *Exposure at Default Model*

(1) Description

The First Lien Mortgage Exposure at Default (EAD) Model is used to determine the total outstanding loan balance at the time of default. Considering that more than three quarters of the first lien mortgage portfolio reported on FR Y-14M, Schedule A (First Lien) have terms of 30 years or longer, mortgage loans amortize slowly; historically, at any point in time, the average loan reported in the FR Y-14M had a current balance of 80-90 percent of its original balance. Given the slow amortization of first lien mortgages, the Board assumes EAD for first lien mortgages to be the unpaid principal balance of the loan at the start of the projection horizon, in line with the stress testing principles of simplicity and conservatism. Mathematically, this can be stated as in Equation C6:

Equation C6 – Exposure at Default Model Specification

$$EAD = UPB_0$$

where UPB_0 represents the unpaid principal balance of the loan at the start of the projection horizon.

(2) Support for Model Decisions

First lien mortgages are assumed to have EAD equal to the outstanding loan balance at the start of the projection period. Because of the slow rate of amortization for first lien mortgages with lengthy terms, this assumption produces reasonable estimates of EAD, even though it does not account for any amortization of the loan during the projection horizon as borrowers make scheduled payments.

Given the long terms and slow amortization schedules of first lien mortgages, this treatment is reasonable. However, because the Board does not account for the small amount of expected amortization during the projection horizon period, the assumption is conservative. This conservative approach is reasonable and in line with the stress testing principles. This is because, in addition to the slow amortization rate for first lien mortgages making scheduled payments, the Board also considers that among defaulted loans, amortization will be slower than the scheduled rate. This is because when borrowers become delinquent and then default, they are by construction missing scheduled payments, stalling the amortization process.

Additionally, accounting for amortization would require the development of a more complex model, reducing interpretability of results and increasing operational burden and model processing time. Given the limited impact and the lack of certainty about the true EAD, the Board aligns with the Stress Testing principles of conservatism and simplicity to assume that EAD is equal to unpaid principal balance at the start of the projection horizon.

(3) Adjustments and Data Cleaning Steps

No data adjustments are necessary in the First Lien EAD Model.

(4) Alternatives

An alternative approach was analyzed which incorporated projected amortization into a proposed EAD model. Incorporating amortization would generally reduce EAD as balances on term loans decline over time.

Despite the potential advantages of accounting for amortization, the Board determined that the benefits of accounting for amortization do not outweigh the costs. The impact of amortization on first lien mortgage balances over short time horizons is small, as mortgages tend to have long terms where balances decline slowly. Additionally, EAD is set to project balances of defaulting loans; because default is associated with the borrower failing to make payments, as loans proceed to default, balance decline stalls. Meanwhile, accounting for amortization would require the development of a more complex model, reducing interpretability of results and increasing operational burden and model processing time. Given the limited impact and the lack of certainty about the most likely realized EAD, the Board aligns with the Stress Testing principles of conservatism and simplicity to assume that EAD is equal to unpaid principal balance at the start of the projection horizon.

(5) Questions

Question C9: The Board is seeking comment on whether it should model the amount of balance that is amortized during the projection period, as opposed to setting first lien exposure at default to the principal balance at the start of the projection period.

d. Model Integration and Projection

(1) Description

With the PD, LGD, and EAD models defined, the next step is to apply these models to project losses in the supervisory stress test. This section describes the assumptions used in the process of integrating the different models together, and accounting for edge cases for which specific assumptions are applied.

The model projects loss rates and payoff rates by applying the PD, LGD, and EAD models to loans from the FR Y-14M First Lien schedule. In each quarter, the PD model produces a probability of default and a probability of payoff for each loan. The projected losses for a loan in a given quarter are the product of PD, LGD, and EAD in that quarter. The projected payoff rate for a loan is directly produced by the PD model.

Next, the loan-level default and payoff projections are aggregated. Projected paid-off balance, defaulted balance, and total balance are summed for each firm. These totals are split into purchased credit deteriorated ("PCD") balances and balances that are not purchased credit deteriorated ("non-PCD") based on the "Purchased Credit Deteriorated Status" variable[258] reported in the FR Y-14M. For a given firm, loss and payoff balances are divided by total balances separately for PCD and non-PCD balances to produce loss and payoff rates for each group.

Loans that are in defaulted status at the start of the projection horizon (e.g., are already 180 or more days delinquent) are treated separately. These loans are assigned a PD of 100 percent, reflecting that they have already defaulted; the LGD model is applied as of the start of the projection horizon to project loss severity. Losses for defaulted loans are set to equal the

[258] FR Y-14M, Schedule A.1, Line Item 92. Accounting practices vary for loans purchased credit deteriorated from other loans.

balance at the start of the projection period, multiplied by the projected LGD. To smooth out the impact of losses on defaulted loans, these losses are divided evenly among the first six projection quarters (this is further supported in Section C.ii.d.(2)). As these loans have reached default already, the model does not assign any probability of these loans paying off.

Finally, the model assumes that firms will not incur losses on loans insured by government programs, such as FHA and VA loans. Loans that are covered by government programs protect mortgage lenders in the case of borrower default. Further support for this assumption is available in Section C.ii.d.(2).

In addition to projecting losses on the portfolio of loans reported on FR Y-14M, Schedule A (First Lien), referred to as the "existing portfolio," the model is used to project losses on a hypothetical portfolio of new originations. New origination loss rates and payoff rates are projected similarly to existing portfolio loss and payoff rates. The loan and borrower characteristics of new originations are assumed to remain consistent with those of the existing portfolio, consistent with the stress test assumption of a constant balance sheet, with the following exceptions that are necessary to contemplate the behavior of new originations:

- Certain loans are excluded from the new origination portfolios. Loans that were recently returned to lender portfolios from GSEs (Freddie Mac and Fannie Mae) or private label securitizations are excluded, as are loans originated prior to 2008. These loans are not likely to be representative of new originations, which by definition are more recent vintages and would not have time to be sold to a GSE or private label securitization and then returned to a firm's portfolio, which generally occurs when there are underwriting defects in a loan.
- New originations are assumed to be current (not delinquent), as it takes time after origination for a loan to progress to delinquency.
- The loan age field is reset to zero, reflecting that new originations will by construction be unseasoned. Other time-varying fields, such as time before initial ARM reset and "burnout," are reset as well.
- As new originations are assumed to be originated during the projection period, any fields for loan vintage are reset accordingly.
- Option ARM loans are assumed to be re-originated as traditional ARMs, due to the limited availability of Option ARMs in the current market.

- Origination macroeconomic variables (such as HPI at origination and interest rates as of origination) are reset to be based on the interest rate immediately prior to the start of the projection period.

The result of this process is a dataset that produces, for each reporting firm, three projected loss rates and three projected payoff rates, corresponding to each of: existing non-PCD loans; existing PCD loans; and new origination[259] loans.

Additionally, the share of balances to be assigned a conservative loss rate based on missing data, as described in Section C.ii.a.(3), is produced for each firm, separately for PCD and non-PCD balances.

Finally, the sum of OREO losses (as described in Section C.ii.b) is totaled for each firm, separately for PCD and non-PCD balances, and accounted in projections of pre-provision net revenue.

The projections produced in this section are applied in the Retail Loss Aggregation process, detailed in Section C.ii.e.

(2) Support for Model Decisions

The model integration process is generally mechanical, aggregating results from across the model components. This section supports certain parts of the process where assumptions are made.

Existing Defaults Assigned 100 Percent PD, Spread Evenly Over 6 Quarters

For loans that are 180 or more days past due at the beginning of the projection horizon (or trigger other default conditions), the PD model is not applied. This is because the loans have already reached terminal status, so further transitions from default are not possible.

[259] New origination losses are assumed to all be non-PCD.

Spreading losses on loans starting in default across six quarters allows for imminent loan losses to be realized expeditiously, consistent with the principle of conservatism, while avoiding the loans from being charged off all at once at the start of the projection, which would create unreasonably high provision estimates in the first projection quarter.

PCD and non-PCD Loans are Projected Separately

The accounting procedures for PCD and non-PCD loans vary, as PCD loans are credit deteriorated at the time of purchase. Prior to firm adoption of the Current Expected Credit Loss ("CECL") accounting framework, the book value of PCD loans was reduced by the amount of the expected credit loss. To account for this, the supervisory stress test model separates out these balances, and applies an adjustment in Retail Loss Aggregation (see Section C.ii.e for more information) to credit against PCD losses. After the adoption of CECL by firms, this is no longer necessary; however, the continued separation of these balances is not problematic. For this reason, PCD and non-PCD balances are separated, despite the additional complexity it adds to the modeling framework.

No Losses Incurred on Government Guaranteed Loans

Loans insured by government programs cover the lender in the case of a default on the mortgage. Unlike loans with private mortgage insurance, these loans are insured by the U.S. government, mitigating the risk of counterparty default.

In practice, total coverage varies. The largest share of government guaranteed loans is made up of FHA loans, which are fully guaranteed. Almost all of the remainder is made up of VA loans, which have a partial guarantee.

Given that coverage varies across different programs, an alternative assumption would be to adjust the losses on each loan separately based on the exact coverage. However, as coverage amounts vary based on loan characteristics, this more granular adjustment would increase the complexity of the model. Given that most balances covered by this adjustment are FHA loans that are fully guaranteed, and to avoid punitive treatment of loans guaranteed by the government, the First Lien Mortgage model assumes that all losses to the lender due to borrower default on these loans are covered.

New Originations are Generally Assumed to Have the Same Characteristics as the Existing Portfolio

This assumption is consistent with the constant balance sheet assumption applied across the supervisory stress test models, which states that firm balance sheets are expected to remain constant across the stress test horizon. Exceptions are made for certain dynamic variables based on reasonableness; it is unreasonable, for example, to assume a loan will originate as a seasoned loan or that it will behave as a 2008 origination. Macroeconomic variables set based on the origination date are reset as well to better reflect the expected behavior of these loans.

(3) Adjustments and Data Cleaning Steps

No additional adjustments or data cleaning steps are applied.

(4) Alternatives

Given that the model integration process is a straightforward application of the PD, LGD, and EAD components, no specific alternative implementations were considered.

e. Retail Loss Aggregation

(1) Description

Retail Loss Aggregation refers to the process by which the Board uses the outputs described in the previous sections to produce final projections of loss dollars. In particular, the process begins with the reported portfolio balances, the projected loss rates, and projected payoff rates described in Section C.ii.d for each quarter and for each firm participating in the supervisory stress test reporting data on FR Y-14M, Schedule A.1 (First Lien)—both for the existing portfolio and the projected new origination Portfolio. From there, the Board applies a series of calculations and adjustments, described in detail below. The output of the Retail Loss Aggregation process is a final projection of loss dollars for each firm in the portfolio in each quarter.

Calculation of Existing Portfolio Losses and Payoffs

In Retail Loss Aggregation, the projected loss rates are applied to the balances of first lien mortgages produced by the balance sheet line-item projections calculator based on data reported in FR Y-14Q, Schedule M.1 (Balances).[260] In particular, first lien balances are calculated as the sum of balances reported on line item 1.a.1.a, column A (first mortgages, denoted by CALBP328) and line item 1.a.1.b, column A (first lien HELOANs, denoted by CALBP332) on this schedule. These loss rates are computed separately for non-PCD and PCD balances. Total PCD and non-PCD balances are derived from FR Y-14Q, Schedule M.3.[261] Subject to the adjustments described below in this section, existing portfolio loss rates (separately for PCD and non-PCD) are multiplied by these balances in each of the 13 projection quarters to produce

[260] *See* the Balances Model Description.

[261] Formally, the unpaid principal balance of PCD loans in a portfolio is taken directly from FR Y-14Q, Schedule M.3, Part I (the sum of line item 1.a.1.a, column D, denoted by CALBR754, and line item 1.a.2.b, column D, denoted by CALBR758), and the unpaid principal balance of non-PCD loans is calculated as the book value reported on FR Y-14Q, Schedule M.3, Part I (the sum line item 1.a.1.a, column A, denoted by CALBR751, and line item 1.a.1.b, column A, denoted by CALBR755) plus the total first lien cumulative interim loan losses reported on Part II of FR Y-14Q, Schedule M.3 (the sum of line item 1c, denoted by CASRKY25, and line item 2c, denoted by CASRKY26). The calculation used for non-PCD loans may not exactly align with the unpaid principal balance reported on FR Y-14Q, Schedule M.3, Part I (column B); however, this is appropriate to account for other accounting adjustments to book value that are unrelated to past or future credit losses.

existing portfolio loss dollars. Similarly, payoff balances for the existing portfolio are produced by multiplying the modeled payoff rates by these balances.

Calculation of New Origination Losses and Payoffs

With projected loss and payoff balances calculated for the existing portfolio, new origination balances in each quarter are calculated as the sum of the dollar amount of payoffs and losses in that quarter from the existing portfolio (as well as any additional loss or payoff amounts from new originations in previous quarters). This process implies that through the projection horizon, firms will originate loans equal to the total amount of balances that rolled off in a previous quarter, consistent with the supervisory stress test assumption of a constant balance sheet. Furthermore, the path of loss rates and payoff rates for each vintage of new originations is assumed to be identical. For example, the loss rate and payoff rate path for loans that originated in the second projection quarter is the same for those that originated in the fifth projection quarter. The sum of existing non-PCD, existing PCD, and new origination loss dollars is the total loss dollar amount for the portfolio, subject to the below adjustments.

Calculation of Losses on Commercial Loans

As noted in in Section C.ii.a.(3), certain loans reported on FR Y-14M, Schedule A.1 (First Lien) are commercial loans (representing under 1 percent of total balances) and are therefore not modeled using the First Lien Model. Losses are assigned separately in Retail Loss Aggregation. To assign losses on commercial loans, the following procedure is used. First, the share of balances reported on FR Y-14M, Schedule A.1 (First Lien) that are commercial are calculated for each firm, both among PCD and non-PCD loans (referred to as “Commercial Weights”). Next, separately for PCD and non-PCD balances, the share of severely delinquent loan balances—defined as loans that are 90 or more days delinquent or in foreclosure or repossession—is calculated for both commercial and non-commercial loans. It should be noted that severely delinquent balance shares are calculated at the industry level rather than by firm; as certain firms have very small commercial portfolios, the calculated shares can become unreasonably extreme at the firm level. With these severely delinquent industry shares calculated, separately for PCD and non-PCD loans, the ratio of the severely delinquent shares among commercial and non-commercial loans is calculated (referred to as "Commercial Factors").

With the Commercial Weights and Commercial Factors calculated, they are next used to assign losses to commercial balances. To implement this, for each firm, separately for PCD and non-PCD balances, the share of balances that are commercial (defined by the Commercial Weight) is assigned losses equal to the modeled loss rate for that firm (separately for PCD and non-PCD balances) multiplied by the PCD or non-PCD Commercial Factor. For instance, if a firm's modeled non-PCD loss rate is 5 percent, the firm's Commercial Weight is 10 percent, and the industry Commercial Factor is 1.1x, the firm's non-PCD loss rate inclusive of the commercial adjustment is calculated as 5 percent multiplied by 90 percent (the Commercial Weight subtracted from one) plus 5 percent multiplied by 10 percent (the Commercial Weight) multiplied by 1.1 (the Commercial Factor), or 5.05 percent. This adjusted loss rate is multiplied by portfolio balances using the procedure described in the beginning of this section used to calculate total loss dollar estimates. This calculation is described mathematically in Equation C7:

Equation C7 – Commercial Loan Losses

$$
\begin{aligned}
Loss\ Rate_{s,i,t} = {} & (1 - Commercial\ Weight_{s,i}) * Modeled\ Loss\ Rate_{s,i,t} \\
& + Commercial\ Weight_{s,i} * Modeled\ Loss\ Rate_{s,i,t} \\
& * Commercial\ Factor_{s}
\end{aligned}
$$

where:

- s refers to either the PCD or non-PCD segment;
- i refers to the firm, t refers to the projection quarter;
- $Loss\ Rate_{s,i,t}$ refers to the firm's loss rate in either the PCD or non-PCD segment;
- $Commercial\ Weight_{s,i}$ refers to the commercial weight, as defined in the previous paragraph;
- $Modeled\ Loss\ Rate_{s,i,t}$ refers to the firm's loss rate in either the PCD or non-PCD segment in a given projection quarter, as calculated in Section C.ii.d; and
- $Commercial\ Factor_s$ refers to the commercial factor in either the PCD or non-PCD segment, calculated at an industry level.

Application of Credits Against Already-Realized Losses

Next, both PCD and non-PCD losses (inclusive of the commercial adjustment described above) are netted against certain credits for loans that have already been charged off. Failing to consider these credits would lead to double counting of these losses. Credits are applied differently between PCD and non-PCD balances. For PCD balances, credits are assumed to be equal to the difference between the unpaid principal balance and the book value[262] reported on FR Y-14Q, Schedule M.3.[263] Credits are applied on a "first-loss first-credited" basis. In other words, the amount of PCD losses is reduced by the value of credits until no further credits remain; at that point, no further reductions are made. For non-PCD balances, credits are assumed to be equal to the "Cumulative Interim Loan Losses" reported on Part II of FR Y-14Q, Schedule M.3, which equal the balances the firm has previously charged off against loans that

[262] Unpaid principal value is the total principal amount outstanding as of the end of the reporting period (separated by PCD vs. non-PCD) and does not include any accounting-based write-downs. The book value is consistent with the values reported on FR Y-14Q, Schedule M.1 and does include certain accounting adjustments.
[263] Historically, the difference between unpaid principal balance and book value on this schedule for the predecessor of PCD loans ("PCI" loans) was reflective of the credit discount marked at the time of purchase. However, under the CECL accounting standard, this is no longer case, as the discount is now instead included in the allowance for credit losses. The Board analyzed the process of assigning credits for PCD loans and assessed that the materiality was small; therefore, the procedure described above is used. However, in the future, the Board may adjust the process to account for reporting changes driven by firm adoption of CECL.

are still active on its balance sheet.[264] The Board applies these non-PCD credits evenly over the first six projection quarters, to be consistent with the treatment of defaulted loans in the supervisory stress test. Net losses for a given firm are calculated as the adjusted losses calculated in the previous paragraph minus the credits described in this paragraph.

Calculation of Projected FDIC Shared Loss Agreement Payments

Finally, losses are reduced to account for coverage provided by shared loss agreements (SLAs) with the Federal Deposit Insurance Corporation (FDIC). As part of the resolution of a failing institution, the FDIC may enter into an agreement with the purchaser to absorb a portion of certain losses on specific assets.[265] To avoid unduly penalizing firms for loan losses covered by SLAs, the Board reduces first lien mortgage losses to account for this coverage. In particular, the Board has proposed collecting the balances of first lien mortgages covered by SLAs on the FR Y-14Q.[266] The share of losses covered by the SLAs are assigned based on the terms of the individual SLA reported by the FDIC. Finally, loss rates on the portion of the balance covered by the SLA are assumed to be the same as the loss rate on the entire existing portfolio.[267] In total, losses on a portfolio are reduced by the covered percentage of the projected losses on covered balances, as calculated above.

Treatment of Immaterial and Missing Portfolio Data

The above process produces loss dollars for firms reporting data on FR Y-14M, Schedule A (First Lien); however, certain firms who report first lien mortgage balances on FR Y-14Q,

[264] Following the adoption of CECL by firms, this field no longer is limited to Cumulative Interim Loan Losses on non-PCD balances; however, in practice, the vast majority of balances are non-PCD.
[265] *See* "Shared Loss," Federal Deposit Insurance Corporation, https://www.fdic.gov/franchise-sales/shared-loss.
[266] *See* proposed instructions for FR Y-14Q, Schedule M.4. Until these instructions are finalized, the Board may collect this information via a special data collection.
[267] SLA balances are assumed to be cover equivalent shares of PCD and non-PCD balances (and equivalent shares of CRE balances within these categories). No adjustment is made for SLA coverage of new origination loans, as new originations are by construction not purchased from the FDIC.

Schedule M.1 Balances do not report on FR Y-14M, Schedule A.[268] For firms not reporting on the FR Y-14M, Schedule A that are not required to do so, balances are assigned, consistent with Section 2.10 of the Stress Testing Policy Statement, the loss rate path and payoff rate path of the firm with the 50th percentile loss rate, among firms reporting FR Y-14M, Schedule A (First Lien). These loss rates and payoff rates are calculated separately for PCD and non-PCD exposures; because new originations are assumed to be non-PCD exposures, the new origination loss rate and payoff rates are based on the 50th percentile in terms of existing non-PCD loss rates.[269] With these loss rates and payoff rates assigned, the Retail Loss Aggregation process is applied, as described above.[270] For firms not reporting FR Y-14M, Schedule A (First Lien) and are required to do so, the process is the same as for firms with immaterial portfolios, except that, consistent with Section 2.9 of the Stress Testing Policy Statement, the Board assigns these exposures the loss rate and prepay rate paths of the firm with the 90th percentile loss rate among firms reporting FR Y-14M, Schedule A (First Lien). In either case, if no firm is exactly at the 50th or 90th percentile, respectively, the firm with the loss rate immediately above this level is used.

Additionally, as described in Section C.ii.a.(3), among firms who do report FR Y-14M, Schedule A (First Lien), a portion of the balance may be assigned a conservative loss rate if it cannot be run through the model; criteria for being assigned this loss rate are found in that sub-

[268] Firms are required to report FR Y-14M, Schedule A, First Lien schedule if portfolio balances are material, as defined in the FR Y-14M instructions. Firms with portfolio balances that are below the materiality threshold have the option of submitting or not submitting the schedule. The Board uses reported data to produce loss estimates for firms whenever possible, even if the reporting institution is below the materiality threshold.

[269] In this context, "loss rate" refers to total loss dollars divided by initial portfolio balances, and "payoff rate" refers to the to the total dollar value of payoffs divided by initial portfolio balances. Percentiles are calculated by summing the loss rates over the 13 projection quarters.

[270] Since the commercial weights cannot be calculated for firms not reporting FR Y-14M, Schedule A (First Lien), the Board assumes that immaterial balances are not commercial exposures. This is reasonable, considering the small share of the overall portfolio that consists of commercial exposures. The information required to apply the other adjustments described in this section is available on other schedules that are reported by all firms.

section. This balance is assigned the 90th percentile loss rate path (separately for PCD and non-PCD exposures), as described in the previous paragraph.

Calculation of OREO Losses

Finally, the OREO losses produced in Section C.ii.d are adjusted to account for projected OREO losses on the share of a firm's balances receiving a conservative loss rate, as described in the previous paragraph. To make this adjustment, for a given firm and quarter, the ratio of OREO losses to credit losses among loans that are run through the model is calculated, and this ratio is multiplied by the total balance of loans receiving the conservative (90th percentile) loss rate for that firm in that quarter to approximate the OREO losses on loans receiving the conservative loss rate. The OREO losses on loans receiving the conservative loss rate are added to the total OREO losses calculated in Section C.ii.d to produce total OREO losses for a given firm in a given quarter. Firms receiving the 50th percentile loss rate are assumed to have zero OREO losses; given the intrinsically small impact of First Lien losses on firms sufficiently immaterial to not be required to report FR Y-14M, Schedule A, not accounting for OREO losses for these firms does not substantially impact the supervisory stress test results. OREO losses are one component of pre-provision net revenue (PPNR).

Total losses described throughout this section are used in the downstream Provisions Model[271] to produce estimates of provisions.

(2) Support for Model Decisions

The Retail Loss Aggregation process produces loss estimates using a consistent process across all retail portfolios. This process ensures adherence to principles of the supervisory stress test, including simplicity, consistency, robustness, and the assumption of a constant balance sheet

[271] *See* Section B in the Aggregation Models Documentation (Provisions Model).

throughout the forecast period. The assignment of existing portfolio losses is a straightforward calculation based on the reported data. Support for the other adjustments and calculations is outlined below.

Assignment of New Origination Losses

New origination losses are assigned based on the expected balances of new originations and the calculated new origination loss rate from the First Lien Loss Model. The expected balances of new originations are assigned to be consistent with the assumption of a constant balance sheet through the supervisory stress test horizon. In particular, expected new origination balances in a quarter are set to be equal to the projected run-off from the prior quarter, where the run-off is equal to the sum of projected losses[272] and payoffs in that quarter. The calculated new origination loss rate path relies on the supervisory stress test scenario and assumes that the new origination portfolio is identical to the existing portfolio, except in certain dynamic variables such as loan age and delinquency status are reset. For more details, see Section C.ii.d.

One simplifying assumption in this process is that all new origination vintages are assumed to follow the same loss rate path. As a result, new origination loss rates for all vintages are identical and calculated using the start of the scenario path. There is no variation in new origination loss rates based on when in the projection period the loans are projected to be originated. This may lead to over- or under-prediction of losses of certain vintages that experience a macroeconomic environment that is not well reflected by the start of the scenario; meanwhile, losses on projected new originations account for less than 20 percent of total

[272] Because LGD can be less than 100 percent, using projected losses instead of projected defaulted balance may underestimate the run-off level. However, the vast majority of run-off is due to payoff balance rather than defaulted balance, so the impact of not accounting for recovered balance is small. Using projected balances reduces the complexity of the process by avoiding the need to pass an additional parameter (default rate) downstream from the First Lien Model through the Retail Loss Aggregation process.

projected losses in recent stress test exercises. Therefore, the single loss rate path is used. Given that new origination losses are a minority of total losses and that loss rate paths are similar at different starting points, the Board has assessed that the impact of using more loss rate paths would be limited.

Treatment of Commercial Loans

As described in Section C.ii.a.(3), commercial loans have different historical behavior than non-commercial loans, and are also frequently missing key fields necessary for modeling, such as the U.S. state of the property.[273] As it is therefore unreasonable to apply the expected loss model to these loans, a different process must be applied to produce loss estimates for commercial loans.

Commercial loans account for a small minority of total balances reported on the FR Y-14M (representing less than 1 percent of total balances). Because of the small number of loans at issue, simplicity is prioritized, as the small number of loans both make it challenging to estimate a model and reduce the benefit of precise model projections. Given the small materiality, scaling losses based on the ratio of severely delinquent balances between commercial and non-commercial loans provides a simple solution that accounts for potential differences in risk levels between commercial and non-commercial loans.

One consideration is that by applying the commercial factors at the industry level rather than the firm level, the model does not account for variation in commercial loan performance across firms. For instance, if one firm has a less risky commercial loan portfolio compared to other firms, this is not accounted for in the model. Despite this limitation, the factors are calculated at the industry level. This is due to the fact that certain firms have very small numbers

[273] These missing fields, including property state, are driven by the reporting instructions, rather than the failure of reporting institutions to report required fields.

of commercial loans; a single commercial loan entering delinquency could significantly impact the commercial factors if they were assigned at the firm level. To avoid this volatility, the industry-level value was used. If commercial loans were to make up a larger share of portfolio balances, a more complex treatment could be justified to ensure predictions are reasonable; given the small balances at issue, the simple approach provides reasonable loss projections for commercial loans.

Finally, commercial weights and commercial factors are calculated separately for PCD and non-PCD balances. This reflects that PCD and non-PCD balances may have fundamentally different behavior, as PCD exposures have known credit deterioration. By separating the calculation, the model ensures that commercial loan losses are set based on portfolio trends rather than differences in the shares of commercial and non-commercial loans that are PCD.

Application of Accounting Credits

As noted earlier in this section, accounting credits are assigned separately for PCD and non-PCD loans. This process is justified by the separate accounting treatment for PCD loans from other loans. Prior to the adoption of the CECL accounting standards by firms, the predecessor of PCD loans ("PCI" loans) had their book value reduced by the amount of expected credit losses at the time of purchase.

As firms have adopted CECL, the distinction has become less meaningful for the application of accounting credits; however, the separation is maintained in the First Lien Model due to limited materiality and resource constraints.

For non-PCD loans, credits are based on the Cumulative Interim Loan Losses reported on Part II of FR Y-14Q, Schedule M.3. While the adoption of CECL by firms means that Cumulative Interim Loan Losses are not separated for non-PCD loans, the model assumes that all Cumulative Interim Loan Losses are applied to non-PCD loans based on the fact that non-PCD loans account for the vast majority of balances. Additionally, in previous periods when PCD and non-PCD Cumulative Interim Loan Losses were separated, most of the total Cumulative Interim Loan Losses were also non-PCD. Cumulative Interim Loan Losses refer to write-downs on loans that remain active on a bank's portfolio, potentially due to the loan being in the repossession or charge-off process. Since the firm has already accounted for these losses, they should not further reduce the firm's capital levels. The model applies non-PCD credits evenly over the first six quarters of the projection horizon. This is intended to be analogous with the treatment of loans in defaulted status at the beginning of the projection period (see Section C.ii.d). Given that Cumulative Interim Loan Losses are likely reported for loans that are already in default, it is reasonable to apply these credits to net against losses projected on defaulted loans. Assigning all the credits in the first projection quarter would be incongruous with the Board's assumption that losses on defaulted loans are spread over many quarters.

For PCD loans, credits are based on the difference between the reported unpaid principal balance and book value reported on FR Y-14Q, Schedule M.3. Prior to the adoption of CECL by firms, this difference was reflective of the credit discount at the time of purchase; since the firm has already accounted for certain credit losses on PCD loans, it is inappropriate to further penalize the firm for such losses. Given that it is unknown how portfolio-level credit discounts are allocated to various PCD loans, these credits are applied on a first-loss first-credited basis until all credits have been applied.[274] However, after the adoption of CECL by firms, the credit discount is no longer removed from the book value; as such, the difference between unpaid principal balance and book value no longer reflects the credit discount. Nevertheless, as the

[274] The amount of accounting credits applied to PCD balances in a given quarter is not allowed to be greater than the total of projected losses in that quarter. This implies that net PCD losses for a given quarter are lower bounded by 0.

assumption that this difference is due to a credit discount has a negligible impact on loss projections, the treatment is maintained.

Treatment of FDIC Shared Loss Agreements

Loans subject to shared loss agreements with the FDIC are partially insured by the government. Balances subject to these agreements can vary substantially over time, based on the rate at which failed banks are disposed by the FDIC and the terms of such dispositions. Because of this insurance, the Board does not assign losses to the portion of covered balances insured by the FDIC. The terms of the agreement are made public by the FDIC; these terms are used to set the specific loss sharing rate for each portfolio for each firm.

The Board uses the share of the portfolio balances subject to a shared loss agreement (SLA), as reported by a firm, to estimate the amount of losses covered by the agreement. This process implicitly assumes that the characteristics of the portion of the portfolio covered by SLAs are identical to that of the rest of the portfolio. If the portion of the portfolio covered by SLAs is notably riskier or less risky than the rest of the portfolio, this may lead to an inappropriate projection of the share of balances covered by the FDIC. However, addressing the potential for differences in portfolio characteristics would require firms to identify individual loans covered by SLAs, which would increase the reporting burden on firms while increasing the complexity of the Board's modeling process. To limit the operational burden for both reporters and the Board, this portfolio level adjustment is used.

Process for Missing and Immaterial Portfolios

The process for missing and immaterial portfolios is consistent with other models throughout the supervisory stress test to produce reasonable projections while mitigating the burden to reporting institutions, and are aligned with the Stress Testing Policy Statement, as described in Section C.ii.e.(1).

Process for Calculating OREO Losses

Given that OREO losses have already been calculated based on the procedure described in Section C.ii.d, the process applied in Retail Loss Aggregation is straightforward. Because the balances receiving the conservative loss rate have not been run through the First Lien Model, OREO losses have not been assigned to these balances. The chosen approach is simple and accounts for the expectation that in addition to the credit losses on these loans, the model must account for OREO losses as well.

For firms receiving the immaterial loss rate, the Board determined that due to the small balances of first lien mortgages at these firms, accounting for OREO losses would not meaningfully impact stress test results. Therefore, to simplify the approach, OREO losses are not projected for immaterial firms.

(3) Adjustments and Data Cleaning Steps

Generally, no data adjustments are needed for this step. However, if a firm's submitted data are too deficient to produce a supervisory loss estimate, the Board assigns a high loss rate to the portfolio balances based on supervisory projections of first lien mortgage losses for other firms, as previously described in Section C.ii.e.(1). In the case that the Board determines the submitted data to be deficient, the Board may assign this high loss rate to the portfolio balances.

(4) Alternatives

A range of alternatives are available both for determining the level of new originations and the treatment of missing data and immaterial portfolios. The Retail Loss Aggregation framework is chosen to produce reasonable, consistent projections that are consistent with the Stress Testing Policy Statement. Alternatives to the specific adjustments are described below.

Assignment of New Origination Losses

The First Lien Mortgage Model assumes that all new origination vintages follow the same loss rate path. However, as each new origination vintage is necessarily originated in a different macroeconomic environment over the course of the scenarios, this assumption limits the ability of the model to incorporate the different risks impacting different vintages of new originations.

An alternative modeling assumption would be to create different loss rate paths for different vintages, by running the model with different macroeconomic scenario paths depending on when in the scenario the loans were originated. While this would provide more precise projections of new origination losses, it would substantially increase the operational complexity of the model. Losses on new originations are a small share of total projected losses, while many of the factors determining losses are loan and borrower characteristics, which would not change, as opposed to the macroeconomic environment, which would. Given the limited impacts and increased complexity of producing more than one new origination loss vector, the single loss path for new originations is maintained to align with the principle of simplicity.

Treatment of Commercial Loans

Commercial loans make up a small share of loans reported on the FR Y-14M; a simple adjustment projects losses on these balances.

One alternative approach is to run commercial loans through a separate model based on the factors that are associated with credit losses specific to commercial loans. For instance, the supervisory stress test Commercial Real Estate (CRE) model could be applied to one-to-four family properties with a commercial purpose. The drawbacks to this approach are operational, as relying on the CRE model would significantly burden FR Y-14 reporters. As the FR Y-14 instructions are written, loans secured by one-to-four family properties are reported together, regardless of the purpose of the loan as commercial or non-commercial. These instructions are consistent with the FR Y-9C instructions. Requiring reporters to separate and reallocate balances based on loan purpose would require adjustments to firms' internal process that are not justified to account for the small amount of balance at issue. Similarly, without adjustment to the reporting procedures, to apply the CRE model to these loans would require the Board to implement an operationally complex adjustment process. Additionally, the CRE model would have to be enhanced to cover one-to-four family mortgages, which are not currently included in the model.

Another approach, which is less complex than producing a complete model for commercial first lien mortgages, is to use the same method, but to assign the commercial factor at the firm level, rather than the industry level. Assigning the factor at the firm level would allow the model to account for firm-specific variation in commercial loan performance. Despite this advantage, the firm specific factor would introduce substantial volatility. As some firms have a small number of commercial loans, a change in a small number of loans' payment status could drastically change the commercial factor to the point where it could notably impact projected losses despite the small size of the portfolio. Given the small materiality of the portfolio (under 1 percent of total balances), stable, reasonable estimates of commercial losses are prioritized; therefore, the factor is calculated at the industry level. The Board may revisit this assumption if balances or projected losses on commercial loans become more impactful in the future.

Application of Accounting Credits

Considering that with firm adoption of the CECL accounting standard, accounting treatments on PCD loans differ from their predecessor, an alternative approach to assigning credits would be to combine PCD and non-PCD balances in the Retail Loss Aggregation process. Combining the balances would be consistent with the instructions for Cumulative Interim Loan Losses, which do not require differentiation of PCD and non-PCD losses. This combination would also eliminate the use of the difference between unpaid principal balance and book value for assigning credits on PCD losses. The Board uses the current approach for operational consistency, considering the limited impact of PCD credits on the supervisory stress test results. However, if PCD balances and credits increase in the future, the Board may update the procedure to combine PCD and non-PCD balances.

Treatment of FDIC Shared Loss Agreements

As noted in Section C.ii.e.(2), applying the FDIC SLA adjustment at the loan level, rather than the portfolio level, would allow more granular assessment of losses on covered balances. A loan-level adjustment would allow consideration of whether the portion of the portfolio subject to the SLA is more or less risky than other loans in the portfolio. Despite these advantages, the Board determined that a simpler approach relying on portfolio-level balances would reduce reporting burden and align with the stress testing principle of simplicity while still appropriately considering the insurance provided by shared loss agreements.

An additional alternative to the treatment of loans covered by FDIC SLAs is to treat payments from the FDIC to cover losses as non-interest income, a component of PPNR, rather than to net the FDIC coverage against credit losses. This distinction likely has no impact on projected firm capital levels, as increases in credit loss expenses on the covered assets would be offset by the income recognized from the increased asset value of the FDIC SLA. Given that the impact of both approaches is likely identical, and that accounting for the SLA within the credit loss and allowance calculation reduces the Board's operational burden, the supervisory stress test models account for the SLA using the methodology described in this section.

Process for Missing and Immaterial Portfolios

The process for missing and immaterial portfolios is set to be consistent with other models used in the supervisory stress test. Alternative values could be applied; however, the Board determined that a consistent approach ensured fair treatment of firms across different business lines.

Process for Calculating OREO Losses

The assignment of OREO losses in Retail Loss Aggregation is a simple approach to account for losses on balances assigned the conservative or immaterial loss rates. While the Board considered alternatives, such as assigning OREO losses to immaterial balances, ultimately, the Board determined that due to the small impact of these OREO losses, a simple approach is preferable. Similarly, while there are plausible alternative calibrations of OREO losses for balances receiving the conservative loss rate, the chosen approach is simple and appropriately accounts for the presence of OREO as well as credit losses on these balances.

(5) Questions

Question C10: The First Lien Mortgage model separates losses into PCD and non-PCD exposures. With the adoption of CECL by firms changing the reporting practices for Book Value and Cumulative Interim Loan Losses, should the Board continue to separate these exposures for the purposes of determining accounting credits?

Question C11: Should the Board consider a different process for assigning losses to loans with a commercial purpose instead of using the commercial weights and industry commercial factor described in this section?

Question C12: Should the Board consider a different process for calculating the share of projected first lien losses covered by shared loss agreements with the FDIC?

iii. Key Assumptions for the First Lien Mortgage Loss Model

a. Representativeness of Estimation Data

A key assumption of the First Lien Model is that the data used to calibrate the model parameters are representative of the portfolio data to which the model is applied.

In the case of the PD model, the model parameters are set based on the First Lien PD Data, where filters and sampling are applied to align the properties of the population of loans with that of the FR Y-14M data used to project losses in the supervisory stress test. The model is estimated over a 20-year period, encompassing multiple business cycles and different economic environments. Given the similarities in the loan population of the estimation data with the FR Y-14M data and the inclusion of both historical and recent data, the Board considers the estimation data representative.

One consideration is that the data used to estimate the PD model includes the periods covered by the COVID-19 pandemic. This is despite the unique challenges associated with the behavior of the portfolio given the economic environment during the COVID-19 pandemic. During this period, home prices stayed elevated, and the unemployment rate initially increased at a historic pace and then declined sharply from its peak. Meanwhile, due to forbearance programs offered by lenders, many borrowers missed payments on their loans, which may not be reflective of inability to pay. This combination of increased delinquency (including borrowers who might have stayed current absent forbearance), high home prices and temporarily high unemployment is challenging for incorporation into the model.

Academic research corroborates the view that the economic distortions in 2020 and the years following are significant, and that the observed relationships between the economic environment and borrower behavior during this period are unique to it. For example, Stock and Watson (2025) find that the COVID shock was notable, but had "largely disappeared by late 2022."[275] This finding raises concerns that if data covering 2020-2022 are used to estimate the model coefficients, these coefficients may be impacted by the distortions that caused these unusual observed relationships.

Despite these concerns, ending the estimation in 2019 could potentially lead to model parameters that do not reflect the current portfolio, as such a model would exclude recent periods. This could lead to model projections that do not accurately reflect the true level of risk. To account for concerns about distortions during the COVID-19 pandemic period, while ensuring that recent data is incorporated when estimating the model coefficients, the Board applies a treatment to observations in 2020 and 2021 to account for these distortions.[276] More information on this treatment is available in Section C.ii.a.

In the case of the LGD model, representativeness concerns are greater, both due to the population of loans used to estimate the model parameters and the time periods included in the model. Despite these concerns, the model continues to produce reasonable, appropriate results.

[275] Stock, J. and M. Watson (2025). "Recovering from COVID," NBER working paper 33857.
[276] The treatment is applied to 2020 and 2021, but not 2022, based on the Board's analysis that distortions in the housing market mostly were resolved by the end of 2021. In particular, forbearance rates fell to close to zero by the end of 2021.

While the Timeline Model data source is the same as that of the PD Model, the Loss Severity Model relies on data from loans included in private label securities and mortgage-backed securities owned by a GSE. The Board uses weighting to align the characteristics of these loans with those reported on FR Y-14M, Schedule A (First Lien); however, it is plausible that the unobservable characteristics of these loans differ, and it is also possible that servicers treat securitized loans systematically differently than they would portfolio loans. Despite these concerns, the Board relies on these data sources due to their lengthy, robust history of first lien losses, which is not available in other sources. The model is informed by the Board's experience and expertise, review of academic literature and industry research, as well as monitoring performed by the Board; based on these factors, projections of First Lien LGD are consistent with expectations.

Also, the data used to calibrate the LGD model does not include data in 2020 and after. In the case of the Timeline Model, this is due to unique challenges associated with the behavior of the portfolio given the economic environment during the COVID-19 pandemic, as described above. While the COVID shock affected the PD Model as well, the concerns for the Timeline Model were more fundamental. Due to foreclosure moratoria and other government programs, liquidation timelines extended sharply, in a manner inconsistent with historical behavior or expectations of future behavior. In the case of the Loss Severity Model, the impacts of the pandemic on model performance were less severe; however, the strength of the housing market in recent years has sharply limited the number of liquidations observed. As noted in Section C.ii.b.(3) less than 15 percent of liquidations observed in the data have occurred since 2015, when the estimation sample currently ends.

In this choice of estimation sample, the Board assumes that the estimates are appropriate despite not incorporating more recent data. To assess this risk, the Board relies on analysis comparing projections from the model to observed LGD among loans that liquidated in more recent periods. Results indicate that model performance remains stable and that LGD estimates remain appropriate.

One consideration in modeling LGD is that a large share of observed liquidations occurred during and immediately following the 2008 financial crisis. Therefore, while adding additional periods to the sample would add additional information to the model, the changes to the model parameters would be small given that the majority of the sample would remain unchanged.

D. Home Equity Model

i. Statement of Purpose

The Domestic Home Equity Loan Loss model (Home Equity Model) is used to project loan losses and provisions on domestic home equity exposures, which include closed-end junior-lien home equity loans (HELs) and home equity lines of credit (HELOCs), which are revolving, open-ended loans. HELs and HELOCs (the two home equity “products” or “product types”) are secured by one- to four-family residential real estate located in the United States, as defined by the FR Y-9C, that are held for investment at amortized cost.

The Home Equity Loan Loss model is important for accurately assessing whether firms would be sufficiently capitalized in a severe stress scenario, because stress in the residential real estate sector could lead to significant losses to HEL and HELOC portfolios. Residential real estate, including home equity exposures, was exposed to significant stress during the 2008–2009 financial crisis. Delinquency rates for home equity loans during this period peaked at 5 percent for HELOCs and at 12 percent for HELs, demonstrating the potential for firms to incur substantial losses on home equity exposures during a period of prolonged housing market stress.[277] While balances on HELs and HELOCs have declined since this period, firm balance sheets could still be negatively impacted if exposed to high loss rates on the home equity balances that do remain on firm portfolios.

The Board estimates the Home Equity Loan Loss Model using historical data on HEL and HELOC payment status and loan losses, loan characteristics, and economic conditions. The model projects losses at the loan level with an expected-loss framework, as described in Section III.A of the Enhanced Transparency and Public Accountability Proposal, using data on firm-reported loan characteristics from the FR Y-14M report and economic conditions defined in the Board's supervisory stress test scenarios. All firms with material portfolios are required to report data on FR Y-14M, Schedule B (Home Equity).[278] A separate calculation is used to project losses on firms with home equity balances that do not report data on FR Y-14M, Schedule B (Home Equity); this calculation is detailed in Section D.ii.e.

The expected-loss framework consists of a PD component, an LGD component, and an EAD component. Each of these components is projected using models, as detailed throughout this model description. The model projects PD, LGD, and EAD by applying the model parameters, along with some adjustments described in this model description, to specific loans

[277] *See* Lee, Mayer, and Tracy (2012).
[278] For firms subject to category IV standards, material portfolios are defined as those with asset balances greater than $5 billion or with asset balances greater than ten percent of Tier 1 capital on average for the four quarters preceding the reporting period. For firms subject to category I, II, or III standards, material portfolios are defined as those with asset balances greater than $5 billion or asset balances greater than five percent of Tier 1 capital on average for the four quarters preceding the reporting period. (Source: FR Y-14M instructions, page 4).

from the FR Y-14M regulatory report. The model outputs projected losses under the hypothetical scenario.

ii. Model Description

The Home Equity Model projects loan losses and provisions on home equity loans and home equity lines of credit secured by one- to four-family residential real estate located in the United States, as defined in the FR Y-9C, using an expected loss framework.

As described in more detail in Section D.ii.a, the PD model projects the probability that a loan transitions to a different payment status (i.e., current, delinquent, default, and paid off; alternately referred to as "states" in this document), based on the prior status of the loan as well as characteristics of the loan and the macroeconomic environment. For modeling purposes of the supervisory stress tests, the Board defines HELs and HELOCs as in default when they are 180 days or more past due, or if the loan status is marked as "real estate owned" (REO).[279] The Board defines HELs and HELOCs as delinquent when they are 90 days past due or in foreclosure proceedings, unless they meet the definition of default. Current and delinquent loans may also transition to paid off status if they are paid in full.

The Board estimates separate PD models for the two product types, HELs and HELOCs. At each point in time, each model uses a regression framework to estimate the probability that a loan transitions from one payment status to another status (e.g., from current to delinquent or from delinquent to default) over a single quarter.

The model generates a probability of default and payoff during a quarter, conditional on the loan's payment status at the end of the prior quarter. The model assumes default and paid off

[279] A loan status of "REO" indicates that the lender has taken possession of the collateral.

to be terminal payment statuses and that loans in the model cannot transition out of those payment statuses. Support for treating these statuses as terminal is available in Section D.2.a.(2). Mathematically, the model is specified in Equation D1:

Equation D1 – Home Equity PD Model Specification

$$PR\left(S_{i,t+1} \middle| S_{i,t}\right) = f\left(X_{i,t}, Z_t\right)$$

where:

- *i* represents the loan;
- *t* represents time;
- $S_{i,t}$ represents the status of loan *i* in time *t;*
- $PR\left(S_{i,t+1} \middle| S_{i,t}\right)$ represents the probability (PR) that the loan is in a given payment status *S* in period *t+1* given the payment status *S* in period *t*;
- $X_{i,t}$ represents loan and borrower characteristics; and
- Z_t represents one or more of the macroeconomic variables included in the supervisory scenarios.

Collectively, these models project a probability of default for each loan, conditional on product type, initial payment status, loan and borrower characteristics, and economic conditions over the projection horizon. Section D.ii.a.(2) contains a detailed description of the variables and assumptions used to fit the PD model equations, while Section D.ii.a.(4) contains a detailed discussion on alternative models that the Board has considered.

The LGD model is described in detail in Section D.ii.b. The LGD of a loan is calculated as the unpaid principal balance (UPB) on the loan at default minus net recovery after senior-lien payout. The net recovery after senior-lien payout is calculated as the proceeds from the liquidation sale net of foreclosure costs, less the balance of any senior liens on the property.

Proceeds from liquidation are calculated by subtracting the senior-lien balance from the total recovery amount estimated by the First Lien Timeline and Loss Severity Models.[280]

The Board assumes EAD for HELs to be the UPB of the loan at the start of the projection horizon. The EAD for HELOCs is determined as follows. HELOCs that have been permanently closed or have reached the end-of-draw period are essentially closed-end loans. For these HELOCs, the Board assumes EAD to equal the UPB at the start of the projection horizon. For all other HELOCs, the Board sets EAD to the higher of the UPB at the start of the projection horizon and the original credit limit. These assumptions are aligned with the principles of simplicity and conservatism from the Stress Testing Policy Statement; additional details on the EAD model and support for the Board's approach is available in Section D.ii.e.

The model projects PD, LGD, and EAD by applying the coefficient estimates to specific loans from the FR Y-14M regulatory report to produce loss rates; the PD model also produces rates at which loans are projected to payoff ("payoff rates"); see Section D.ii.d for more details. These loss rates and payoff rates are then applied in a process called "Retail Loss Aggregation," detailed in Section D.ii.e, to project loss dollars using balances produced by the balance sheet line-item projections calculator based on data reported in FR Y-14Q, Schedule M.1 (Balances).[281] Total loss dollars are projected as the sum of projected losses on the existing portfolio plus the projected losses on projected new origination balances during the projection period. Additional adjustments to losses are made at this stage to account for certain portfolio-level factors reported on the FR Y-14 report.

[280] The First Lien Timeline and First Lien Loss Severity Models are discussed in more depth in Section C.ii.b in the First Lien Model Description.

[281] *See* Section A in the Aggregation Models Documentation (Balances Model).

A detailed description of each of the model components is below. First, the structure, input data, and variables used to define the model are described. Next, support for the modeling decisions, including the model structure and the individual variables included in the model is provided. Then, the data cleaning process and any adjustments applied to the input data are detailed. Finally, alternatives to the chosen modeling approaches are discussed, along with questions to solicit feedback from the public.

a. Probability of Default Model

(1) Description

The Home Equity PD Model projects the probability that a loan transitions to a different payment status (i.e., current, delinquent, default, and paid off), based on the prior status of the loan as well as characteristics of the loan and the macroeconomic environment. The definitions of each of the loan statuses are described above in the introduction to this model description; additional details about how these statuses are observed in the data are provided in Section D.ii.a.(3). The Board estimates separate PD models for the two product types (HELs and HELOCs). At each point in time, each model uses a regression framework to estimate the probability that a loan transitions from one payment status to another status (e.g., from current to delinquent or from delinquent to default) over a single quarter. In particular, the framework includes five equations, as follows:

- Two of the equations capture the probability of transitioning from current status to delinquent or paid off status. The probability of a loan remaining current is calculated as the probability that the loan does not transition to either of the other statuses.
- Three of the equations capture the probability of transitioning from delinquent status to current, paid off, or default status. The probability of a loan remaining delinquent is calculated as the probability that the loan does not transition to any of the other three statuses.

- Default and paid off are treated as terminal statuses, and loans are not able to transition from these statuses back to other statuses. Support for treating default and paid off as terminal is available in Section D.ii.a.(2).

Together, these equations[282] generate a probability of default and payoff during a quarter, conditional on the loan's payment status at the end of the prior quarter. Mathematically, the model is specified as discussed below and shown in Equation D2.

Collectively, these models project a probability of default for each loan, conditional on product type, initial payment status, loan and borrower characteristics, and economic conditions over the projection horizon.

To estimate the Home Equity PD Model, the Board uses historical, monthly loan-level data collected by a third-party vendor from several large servicers of home equity products (the "Home Equity Data"). The dataset is comprised of both closed-end home equity loans and home equity lines of credit, and the collected data encompass a significant portion of HELOCs and HELs in the industry.[283] One key advantage of the Home Equity Data compared to other sources, such as historical data reported on FR Y-14M, Schedule B (Home Equity), is the long time series of coverage available. In particular, the Home Equity Data has robust coverage of the home equity market during the 2008 financial crisis period, allowing the model to capture the historical relationships between the macroeconomic environment and default that were observed during this period of severe stress. The Home Equity PD Model is estimated using a 20 percent

[282] Equations are specified as binomial logit equations, each producing an output between 0 and 1 that can be interpreted as a probability.
[283] Based on internal analysis, the Board estimates that the Home Equity Data encompasses around half of the HELOC and HEL industry during the period used to estimate the PD model parameters.

sample of HELOCs and a 30 percent sample of HELs[284] from this dataset, tracking loan performance between January 2002 and December 2017 for loans originated in or after 2002.[285]

Using the characteristics in the data, the model defines the status of each loan in each quarter, as follows:

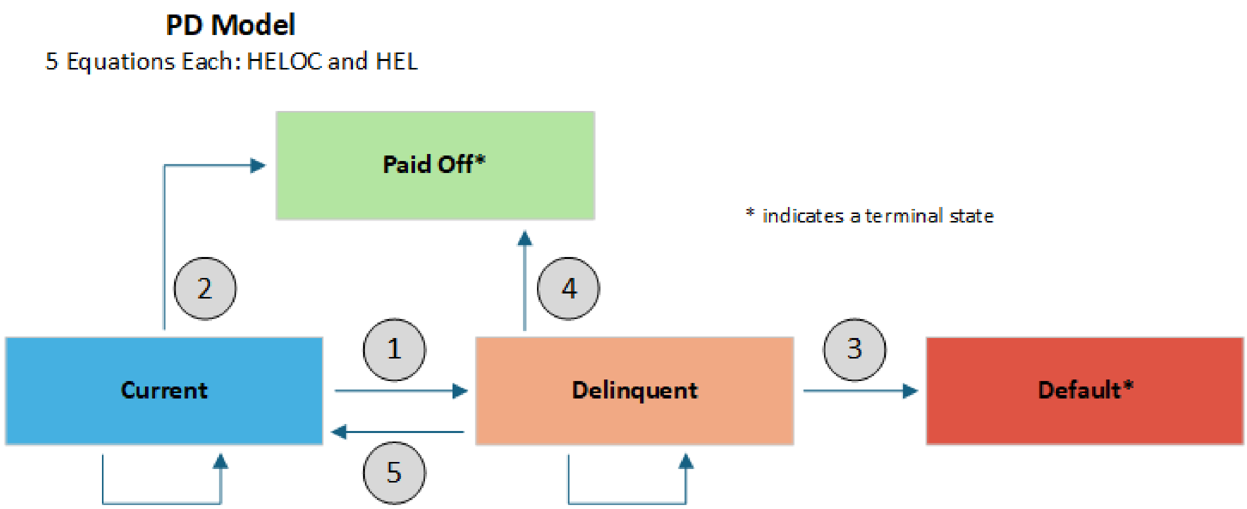
- Default, if the loan is more than 180 days past due, or if the status is marked as "REO," indicating that a lender has taken possession of the property. Loans are also treated as in default if they trigger either of the following criteria:
    - The loan was delinquent in the previous period and payment status is unknown or missing (to account for situations where loans disappear from the panel upon default); or
    - The loan was marked as "paid off" but a charge-off was reported simultaneously or within six months of the reported payoff event (to account for situations in which the full balance of a loan is not paid off).
- Delinquent, if a loan is not more than 180 days past due, but is more than 90 days past due or is in foreclosure proceedings.
- Paid off, if a flag indicating payoff status is observed.
- Current, if a loan is not more than 90 days past due and none of the above criteria are triggered.

With these statuses defined, the model projects the probability of a loan moving from one status to another status. Current loans can remain "current", or transition to "delinquent" or "paid off"; delinquent loans can remain "delinquent", or transition to "current," "default," or "paid off." A series of five equations, marked in the figure below, produce these probabilities. These five equations are estimated separately for HELs and HELOCs, for a total of ten transition equations. "Default" and "paid off" are considered to be terminal statuses, in that loans are not able to transition from these statuses back to other statuses (see Section D.ii.a.(2) for additional support for this modeling choice). This model framework is known as a "state transition model"

[284] A larger sample of HELs is used due to the shrinking size of the portfolio in recent years, which reduces the number of observations, and the larger share of HELs that is filtered out of the data during the data cleaning process (described in Section D.ii.a.(3)).
[285] Discussion of the choice not to include more recent data is available in Section D.iii.a.

framework, in which the loan statuses described reflect states in the model. These transitions can be visualized in Figure D1.

Figure D1 - Home Equity PD Model State Transitions



Each of the ten equations incorporates loan, borrower, and macroeconomic characteristics associated with the transition it predicts. These characteristics are chosen to account for the most important factors in determining the likelihood of the transition. Mathematically, each equation is estimated as the probability of a loan moving to another status, given that the loan either moves to that status or remains in its existing status. See Equation D2 for more details. For instance, the current-to-delinquent ("C" to "L," where "L" is short for "late") equation is the probability that a loan (i) that is current (C) in a given quarter t transitions to delinquent (L) in the next quarter (t+1), given that it is either current or delinquent in the next quarter:[286]

Equation D2 – Home Equity PD Structure

$$\Pr\left(L_{i,t+1}\ |C_{i,t}\ and\ [C_{i,t+1}\ or\ L_{i,t+1}]\right)$$

[286] In particular, in this example, loans that payoff in the next quarter are not included in the data when estimating this equation. Meanwhile, in the current-to-payoff equation, loans are included if they remain current or payoff in the following quarter, but loans that become delinquent are not included in the data used to estimate the current-to-payoff equation. The implementation of this approach is described in more detail in Section D.ii.a.(2).

The full specification of all 10 logit equations is available in Tables D1 – D4. In each of the equations, "Coefficients" refer to the coefficient estimates associated with a given variable, while "Std. Err." refer to the standard errors associated with these coefficients. Each transition is shown separately and denoted using "C" = "Current"; "L" = "Delinquent" (or "Late"); "P" = "Paid Off"; and "D" = "Default." Support for the model structure and the inclusion of the particular variables used in these equations is available in D.ii.a.(2). As described in that section, variables are chosen for inclusion in each equation separately; in many cases, variables that are important to explain certain transitions are not relevant for explaining other transitions. Finally, a discussion of alternative modeling approaches and other variables considered but not included in the model is available in Section D.ii.a.(4).

Note that the variable descriptions in the table below often refer to "knots." Knots are the specific values that separate a variable into segments that are used in a model. These knots are points where the incremental impact of the variable on the output can change. This accounts for non-linear effects across the range of values of a variable, as its impact might not be consistent across all values. For example, in the current-to-late transition model, an origination credit score knot at 680, which accounts for credit score values above 680, reflects the increased sensitivity of delinquency risk to changes in credit score at values above 680 compared to values less than 680.[287] More information about knots, as used in "splines," is available in Section D.ii.a.(2).

More information about the definition of each of these variables is available in Section D.ii.a.(2).

[287] Knot coefficients are interpreted as additive. Following this example, the effect of credit scores above 680 would be based on the sum of the coefficient on the credit score and the coefficient of the credit score knot at 680.

Table D1 - HELOC, from Current

		Current-to-Delinquent		Current-to-Paid Off	
Parameter	**Variable Description**	**Estimate**	**Std.Err.**	**Estimate**	**Std.Err.**
Intercept		-6.4918	0.0689	-2.9386	0.0269
Months on Book	Loan age in months	-	-	-	-
-	Loan age in months, capped at 12	0.1389	0.0017	-	-
-	Loan age in months, capped at 24	-	-	0.0169	0.0001
Origination Credit Score	Origination credit score	-0.0032	0.0001	0.0003	0.0000
-	Origination credit score knot at 680	-0.0059	0.0001	-	-
-	Origination credit score knot at 720	-	-	-0.0007	0.0001
First Lien HELOC	Indicator for first lien HELOC	0.0999	0.0094	-0.2508	0.0029
Wholesale/Broker	Indicator that loan was originated through wholesale or broker channels	0.3640	0.0069	0.0654	0.0033
Purchase Mortgage	Indicator for whether the loan purpose was a purchase	-0.2029	0.0133	-0.1828	0.0059
Updated Combined Loan-to-Value (updated CLTV)	Origination CLTV, adjusted by change in regional house price index since origination	-	-	-	-
-	Updated CLTV knot at 60 percent	0.0242	0.0001	-0.0069	0.0001
-	Updated CLTV knot at 130 percent	-0.0145	0.0003	-	-
Spread at Origination	Difference between coupon rate and index rate (e.g., treasury 3-month) at origination	0.0756	0.0014	-	-
Prime Rate Change	Change in prime rate from origination through the previous quarter	-0.0069	0.0016	0.0406	0.0006
Delinquent Last Quarter	Indicator for delinquency (90+ days past due) in previous quarter	2.6530	0.0169	-	-

		Current-to-Delinquent		Current-to-Paid Off	
Origination Year	Indicator for loan originated in 2006	0.2828	0.0067	-	-
-	Indicator for loan originated in 2007	0.3545	0.0078	-	-
Utilization	Utilization rate (unpaid principal balance as a share of the credit limit), capped at 250 percent	0.0078	0.0002	-0.0574	0.0004
-	Utilization knot at 10 percent	-	-	0.0616	0.0004
-	Utilization knot at 85 percent	0.0704	0.0007		
-	Utilization knot at 95 percent	-	-	0.0532	0.0007
-	Utilization knot at 100 percent	-0.0813	0.0006	-0.0631	0.0007
Unemployment Rate	Year-over-year change in the state unemployment rate	0.0512	0.0018	-	-
House Price Index	Year-over-year percentage change in regional house price index	-0.0200	0.0003	0.0227	0.0001
Seasonality	Indicator for performance period in July–September	0.1461	0.0056	-0.1120	0.0023
-	Indicator for performance period in October–December	0.1256	0.0056	-0.2261	0.0023
Balloon Payment	Indicator for End of Draw (EOD) balloon payment type[288]	0.6692	0.0211	0.2921	0.0070

[288] Formally, the model treats a loan as having a balloon payment if less than five years elapse between the end of the draw period and the end of the loan term. When estimating the model parameters, this variable is set to "1" only if the loan has a balloon payment *and* the loan is no more than two quarters before or after the end of the draw period. When using the model to project losses, a loan is treated as having a balloon payment if the period between the end of the draw period and the end of the loan term, each rounded to the nearest year, is four years or fewer. In producing the model projections, this variable is set to "1" only if the loan has a balloon payment and the loan is no more than four quarters before or eight quarters after the end of the draw period. The Board tested applying the logic used to estimate the model parameters, defining balloon payments based on the period between the end of the draw and the end of the loan term being less than five years, for loans that are no more than two quarters before or after the end of the draw period, in the model projection process and found that losses under the supervisory severely adverse scenario, as a share of risk-weighted assets, changed by less than 0.01 percent for all firms.

		Current-to-Delinquent		**Current-to-Paid Off**	
End of Draw (EOD)	The transition from the draw period to the repayment period, where borrower can no longer borrow funds but must start repaying both the principal and interest.	-	-	-	-
-	Indicator for 5 quarters before EOD	-	-	0.3623	0.0090
-	Indicator for 4 quarters before EOD	-	-	0.4920	0.0088
-	Indicator for 3 quarters before EOD	-	-	0.5575	0.0088
-	Indicator for 2 quarters before EOD	-	-	0.8816	0.0080
-	Indicator for 1 quarter before EOD	-	-	2.0783	0.0057
-	Indicator for hitting EOD	0.6861	0.0236	-	-
-	Indicator for 1 quarter after EOD	1.0205	0.0221	1.4391	0.0076
-	Indicator for 2 quarters after EOD	0.5326	0.0297	0.8791	0.0103
-	Indicator for ≥1 quarter after EOD	-	-	0.5475	0.0053
-	Indicator for ≥2 quarters after EOD	0.4807	0.0158	-	-
Loan Size	Loan amount at origination (in thousands of dollars)	-	-	-0.0001	0.0000
Yield Spread	Spread between 10-year and 3-month Treasury yields in the prior quarter	-	-	-0.0913	0.0011
Cohort	Indicator for observations in 2007	-	-	-0.3262	0.0038
-	Indicator for observations in 2008	-	-	-0.4842	0.0046
-	Indicator for observations in or after 2010	-	-	-0.6999	0.0029

Table D2 - HEL, from Current

		Current-to-Delinquent		Current-to-Paid Off	
Parameter	**Variable Description**	**Estimate**	**Std.Err.**	**Estimate**	**Std.Err.**
Intercept	-	-3.4812	0.0638	-4.4214	0.0188
Months on Book	Loan age in months	-	-	-	-
-	Loan age in months, capped at 12	0.1088	0.0017	0.0860	0.0006
Origination Credit Score	Origination credit score	-0.0069	0.0001	-	-
-	Origination credit score knot at 720	-0.0014	0.0002	0.0031	0.0001
Wholesale/Broker	Indicator that loan was originated through wholesale or broker channels	0.3971	0.0065	0.0290	0.0044
Purchase Mortgage	Indicator for whether the loan purpose was a purchase	0.2327	0.0080	-0.2196	0.0063
Updated Combined Loan-to-Value (Updated CLTV)	Origination CLTV, adjusted by change in regional house price index since origination	-	-	-	-
-	Updated CLTV in the previous quarter	-	-	0.0207	0.0004
-	Updated CLTV in the current quarter knot at 50 percent	-	-	-0.0203	0.0012
-	Updated CLTV in the current quarter knot at 60 percent	-	-	0.0457	0.0016
-	Updated CLTV knot at 60 percent in the current quarter (capped at 160 percent)	0.0228	0.0001	-0.0456	0.0008
-	Updated CLTV in the current quarter knot at 75 percent	-	-	-0.0283	0.0006
Spread at Origination	Difference between coupon rate and index rate (e.g., Treasury 3-month) at origination	0.2093	0.0023	0.0668	0.0013
Delinquent Last Quarter	Indicator for delinquency (90+ days	2.2747	0.0238	-	-

		Current-to-Delinquent		**Current-to-Paid Off**	
	past due) in previous quarter				
Origination Year	Indicator for loan originated in 2006	0.2344	0.0083	-	-
-	Indicator for loan originated in 2007	0.2987	0.0084	-	-
Unemployment Rate	Year-over-year change in the state unemployment rate	0.0634	0.0020	-	-
House Price Index	Year-over-year percentage change in regional house price index	-0.0216	0.0004	-	-
Loan Size	Loan amount at origination (in thousands of dollars)	0.0066	0.0001	-0.0004	0.0001
Treasury Yield Change	Change in 10-year treasury yield from origination through the previous quarter	-	-	0.2237	0.0085
-	Change in 10-year treasury yield from origination through the previous quarter knot at 0	-	-	-0.0966	0.0096
-	Year-over-year change in the 10-year treasury yield	-	-	-0.2775	0.0027
Cohort	Indicator for observations in 2007	-	-	-0.5883	0.0052
-	Indicator for observations in 2008	-	-	-1.2108	0.0069
-	Indicator for observations in 2009	-	-	-1.1270	0.0076
-	Indicator for observations in or after 2010	-	-	-1.1313	0.0063

Table D3 - HELOC, from Delinquent

		Delinquent-to-Default		Delinquent-to-Payoff		Delinquent-to-Current	
Parameter	**Variable Description**	**Estimate**	**Std. Err.**	**Estimate**	**Std. Err.**	**Estimate**	**Std. Err.**
Intercept		-0.7636	0.0822	-2.7119	0.1189	0.3115	0.0172
Months on Book	Loan age in months	-0.0038	0.0002	-	-	-	-
-	Loan age in months, capped at 240	-	-	-0.0088	0.0005	-	-
Delinquent Last Quarter	Indicator for delinquency (90+ days past due) in previous quarter	-0.7513	0.0135	-1.2604	0.0227	0.1620	0.0156
Origination Credit Score	Origination credit score	0.0021	0.0001	0.0032	0.0002		
-	Origination credit score knot at 720	-	-	-	-	0.0020	0.0003
Purchase Mortgage	Indicator for whether the loan purpose was a purchase	0.2984	0.0333	-	-	-	-
Loan Size	Loan amount at origination (in thousands of dollars), capped at $150,000	-0.0001	0.0001	-0.0026	0.0001	-	-
Spread at Origination	Difference between coupon rate and index rate (e.g., treasury 3-month) at origination	-0.0156	0.0035	-	-	-0.0122	0.0038

		Delinquent-to-Default		**Delinquent-to-Payoff**		**Delinquent-to-Current**	
First Lien HELOC	Indicator for first lien HELOC	0.0808	0.0209	-0.8819	0.0449	-	-
Prime Rate Change	Change in prime rate from origination through the previous quarter	-0.0378	0.0034	-	-	-	-
Updated Combined Loan-to-Value (updated CLTV)	Origination CLTV, adjusted by change in regional house price index since origination	-	-	-	-	-	-
-	Origination CLTV knot at 60 percent	0.0086	0.0002	-	-	-0.0072	0.0002
-	Origination CLTV knot at 80 percent	-	-	0.0398	0.0011	-	-
-	Origination CLTV knot at 105 percent	-	-	-0.0295	0.0013	-	-
End of Draw (EOD)	The transition from the draw period to the repayment period, where borrower can no longer borrow funds but must start repaying both the principal and interest.	-	-	-	-	-	-

		Delinquent-to-Default		**Delinquent-to-Payoff**		**Delinquent-to-Current**	
-	Indicator for 5 quarter before EOD	-	-	-0.7982	0.1063	-	-
-	Indicator for 4 quarter before EOD	-	-	-0.7794	0.1064	-	-
-	Indicator for 3 quarter before EOD	-	-	-0.8539	0.1097	-	-
-	Indicator for 2 quarter before EOD	-	-	-0.6627	0.1134	-	-
-	Indicator for 1 quarter before EOD	-	-	-0.6870	0.1199	-	-
-	Indicator for hitting EOD	-	-	-0.3916	0.1162	-	-
-	Indicator for 1 quarter after EOD	-	-	-0.4404	0.0912	-	-
-	Indicator for >=1 quarter after EOD	-	-	-0.9164	0.0626	-	-
Seasonality	Perf Period in July-Sep	-	-	0.2138	0.0194	-	-
-	Perf Period in Oct-Dec	-	-	-0.0993	0.0187	-	-
High Utilization	Indicator for high utilization (>=90 percent)	0.0194	0.0139	-	-	-0.5265	0.0161
Treasury Yield Change	Change in 10-year treasury yield from origination through the previous quarter	-	-	0.1180	0.0122	-	-
Cohort	Indicator for observations in 2007	0.1809	0.0289	0.6248	0.0476	-	-

		Delinquent-to-Default		Delinquent-to-Payoff		Delinquent-to-Current	
-	Indicator for observations in 2008	0.0790	0.0185	0.3120	0.0456	-	-
-	Indicator for observations in 2009	-	-	-0.2700	0.0494	-	-
-	Indicator for observations in or after 2010	-	-	0.3625	0.0522	-	-

Table D4 - HEL, from Delinquent

		Delinquent-to-Default		Delinquent-to-Payoff		Delinquent-to-Current	
Parameter	**Variable Description**	**Estimate**	**Std.Err.**	**Estimate**	**Std.Err.**	**Estimate**	**Std.Err.**
Intercept		-1.4539	0.0875	-0.7656	0.0227	-0.6154	0.0278
Months on Book	Loan age in months	-0.0081	0.0003	-	-	0.0014	0.0003
Origination Credit Score	Origination credit score	0.0038	0.0001	-	-	-	-
Wholesale/Broker	Indicator that loan was originated through wholesale or broker channels	-0.0840	0.0152	-	-	-	-
Purchase Mortgage	Indicator for whether the loan purpose was a purchase	0.0424	0.0181	-	-	-	-
Updated Combined Loan-to-Value (updated CLTV)	Combined loan-to-value updated by regional	-	-	-	-	-	-

		Delinquent-to-Default		Delinquent-to-Payoff		Delinquent-to-Current	
	house price index						
-	Updated CLTV knot at 60 percent in the current quarter (capped at 160 percent)	0.0058	0.0002	-	-	-0.0057	0.0004
Delinquent Last Quarter	Indicator for delinquency (90+ days past due) in previous quarter	-0.8717	0.0155	-1.5301	0.0334	0.3592	0.0200
House Price Index	Year-over-year percentage change in regional house price index	-0.0223	0.0008	-	-	-	-
Treasury Yield Change	Difference between the 10-year Treasury yield at origination and the 10-year Treasury yield in the previous quarter	-	-	0.1383	0.0121	-	-
Cohort	Indicator for observations in 2009	-	-	-1.2534	0.0365	-	-
-	Indicator for observations in or after 2010	0.1987	0.0197	-	-	-	-

To use these models to project PD and payoff rates, the equations are applied to each loan being projected. The probabilities of the individual transition for a given loan's starting status (current or delinquent) are determined using these equations, then are summed. The probability of remaining in the starting status is equal to this sum subtracted from one.[289] This process is repeated throughout the 13-quarter projection period using a process known as a Markov chain. Under a Markov chain process, after each quarter, the probability of a loan being in each of the four model "states" (current, delinquent, paid off, or defaulted) is generated. These probabilities are used as the starting states in the next quarter to create likelihoods that a loan is in each state in a given quarter.

Consistent with the assumption throughout the supervisory stress test of a constant balance sheet,[290] dynamic variables like utilization are expected to remain constant throughout the projection period. Variables that are date-based, like months on book or time until end-of-draw, are updated dynamically based on the amount of time that elapses in the projection.

One complication in this approach is accounting for previous delinquency during the projection period, as in a Markov chain approach, previous delinquency becomes probabilistic. To account for the likelihood that a current loan was previously delinquent in the projection period, transition equations that use previous delinquency are run both assuming previous delinquency and assuming no previous delinquency. The final transition probability is a weighted average of these two estimates that is weighted based on the likelihood that the loan was delinquent in the period before the period being used as the base of the projection, as

[289] Mathematically, this makes the five individual binomial logistic regressions per portfolio equivalent to two multinomial logit regressions, one for each starting status.
[290] The supervisory stress test assumes that a firm's balance sheet will remain constant throughout the projection period; new origination balances are set to be equivalent to the sum of loss balance and payoff balance in a given quarter. For more information on the new origination process, *see* Section D.ii.d.

computed by the model's Markov chain framework. This process ensures that previous delinquency, a key indicator of future delinquency, can be incorporated into the transition model framework.

Losses on defaulted loans are not run through the model, since they have already reached terminal status; these are accounted for separately. To smooth out the losses on these loans, defaulted loans are assumed to be evenly spread over the first six projection quarters. Applying these defaults all to the first quarter would produce unreasonably large shocks, especially when default rates are elevated; smoothing over six quarters allows these defaults to be realized gradually. Additional discussion of the treatment of defaulted loans is available in Section D.ii.d.

(2) Support for Model Decisions

The design and specification of the Home Equity PD Model is supported by a review of the relevant literature and industry best practices, statistical fit, and modeler expert judgment. This section describes both the support for the overall model design as well as the specific variables and transformations included in the model.

Review of Literature

Among research on residential real estate, most focuses on first lien mortgages rather than home equity exposures, given that first lien mortgages are a much larger market and are associated with more widely available data. However, given that there are similarities between the two portfolios—as both involve loans secured by residential real estate—many findings from the literature are broadly applicable across mortgage products.[291]

Academic literature on mortgage default risk dates back to the late 1960s and early 1970s when von Furstenberg (1969, 1970a, 1970b) developed the first academic default risk model.

[291] Like first lien mortgages, home equity products are consumer loans secured by residential real estate; as a result, similar factors impact the likelihood of default and payoff.

The model showed that home equity at the time of origination was the most important predictor of mortgage default. Since then, numerous mortgage PD models have been developed and estimated. Other examples include Demyanyk and Van Hemert, 2011; Elul, Souleles, et al. 2010; and An, Deng and Gabriel, 2021.

The Board draws on the literature in developing the home equity model. One key finding for mortgage modeling is that default and prepayment[292] are two outcome variables that must be modeled simultaneously. This feature is referred to as "competing risks." Some studies treat prepayment and default as seemingly unrelated risks (see, e.g., Quigley and Van Order, 1991; 1995; Deng, Quigley and Van Order, 1996) that can be predicted independently of one another (in other words, an increase in prepayment probability has no impact on default probability); however, these factors are not independent in practice. The below literature discusses different ways of addressing these competing risks.

A natural approach to modeling mortgage performance is the use of a multinomial logit framework. A multinomial logit is a model that allows for the determination of multiple probability outcomes (such as default and payoff), where the combined probability of all the outcomes sums to one. Early studies include Zorn and Lea, 1989; Campbell and Dietrich, 1983; Vandell and Thibodeau, 1985; Archer et al., 1996; 1997; 2002, Calhoun and Deng, 2002; Ambrose and Sanders, 2003; Clapp, Deng, and An, 2006; An, Clapp, and Deng, 2010; Agarwal, Chang, and Yavas 2012; and Rajan, Seru, and Vig; 2015. An alternative way to handle the competing risks using a logit framework is to estimate prepayment and default probabilities separately ("binomial logit" model) and then convert them to multinomial logit probabilities (see

[292] Prepayment occurs when borrowers pay off their loan balance in full prior to the end of the contractual term. The Home Equity Model refers to the paid off status, which more broadly encompasses prepayment as well as loans that are paid off due to reaching their contractual maturity date; however, in practice, prepayment accounts for the majority of loans that pay off.

Begg and Gray, 1984). Using binomial logits reduces the computational complexity compared to a multinomial logit where all outcomes are estimated simultaneously. Logit models are easy to estimate, implement, and interpret. However, one drawback of these models is that they assume that every observation of a given loan is independent ("serial independence"); if specific loans have unobserved differences that increase or decrease their default or prepay risk, these differences will not be accounted for in the model.

Certain extensions of the binomial or multinomial logit approaches can account for the drawbacks described in the previous paragraph. The next paragraphs describe model structures that leverage the statistical properties of binomial or multinomial logit equations in more complex structures.

An alternative approach to modeling mortgage default and prepayment is a proportional hazard model approach, where, for each quarter, the probability of a loan reaching default or prepayment in that quarter is estimated given that default or prepayment was not reached in a previous quarter. Starting with Deng, Quigley, and Van Order, 2000, hazard models with competing risks have become popular in academic research (see Calhoun and Deng, 2002; Deng and Quigley, 2002; Pennington-Cross, 2003; Clapp, Deng, and An, 2006; Deng and Gabriel, 2006; Gerardi, Shapiro, and Willen, 2007). Compared to logit models, hazard models effectively deal with unobserved heterogeneity across loans, as they relax the assumption of serial independence. However, hazard models simply provide the likelihood of reaching the outcome states (in this case, prepayment or default) in each quarter; they do not output the progression of loans between various states of delinquency. This progression is important for use in a supervisory stress test context, where the scenario variables vary in each quarter and can impact loans differently depending on where in the delinquency process they are at any given point in time. For instance, the impact of a sharp decline in house prices in a quarter may be different for loans that have become delinquent in a previous quarter than for loans that are current in that quarter. The structure of the hazard model does not easily allow for this effect to be captured.

A state transition model framework, as used in the home equity supervisory stress test model, resolves the issue of tracking the progression of individual loans, relaxing the assumption of serial independence. This is generally implemented using a Markov chain framework, where loans are probabilistically assigned to each state in each quarter. The state transition model framework consists of equations, such as binomial or multinomial logits, as described earlier in this section, that predict the probability of transitioning from one state to another state, given the starting state. Examples of state transition models in academic literature include Betancourt, 1999. Outside of academia, state transition models have wide use; see industry examples such as Bergantino and Li, 2010; or government applications such as the Department of Housing and Urban Development's Mutual Market Insurance Fund.[293]

State transition models perform well when extensive data are available and computational power is available, as state transition models are computationally complex. One drawback of state transition models relying on Markov chains is that they generally only consider the current state in determining transition probabilities; in reality, the loan's history might be relevant. For instance, a loan with a previous delinquency history may be more likely to fall back into delinquency, even if the loan is current at a given point. The Home Equity PD Model handles this effect with a "limited memory" variable that is set probabilistically during the projection

[293] *See* "Annual Actuarial Review of the FHA Mutual Mortgage Insurance Fund Forward Loans: Fiscal Year 2024," United States Department of Housing and Urban Development, (13 Nov 2024), https://www.hud.gov/sites/dfiles/Housing/documents/2024-MMI-Forward-Loans-Final-Report.pdf.

period. However, this adds substantial computational burden to the model. Despite these burdens, the ability to account for this effect justifies its inclusion.

One paper by Hale, Krainer, and McCarthy (2020) compares model projections using variations of loan-level, bottom-up models (based on binomial logit structures) to "top-down" models that aggregate loans prior to making projections. In particular, the top-down model approach estimates two models where the default rate in a given quarter is based on average loan characteristics and macroeconomic variable values, aggregated to the county and national levels respectively. The paper concludes that the performance of aggregated models can exceed that of loan-level models, although the optimal level of aggregation may vary based on characteristics of the data and of the portfolio.

In addition to providing evidence related to model structure, a review of the literature also provides evidence supporting the identification of the variables that are most important in determining default and prepayment risk. As noted earlier, the amount of home equity available to a borrower (referred to as the mark-to-market loan-to-value or refreshed loan-to-value) is the most important factor in predicting nonpayment. This has been confirmed by studies such as Bajari, Chu, and Park, 2008; Foote, Gerardi, and Willen, 2008; Haughwout, Peach, and Tracy, 2009. Other economic factors also influence default risk. For example, Bhutta, Dokko, and Shan, 2010 distinguish between defaults induced by job losses and other income shocks from those defaults induced purely by negative equity, and they find that both LTV and job loss play important roles in mortgage defaults. Based on these papers as well as independent analysis, the Board includes measures of both updated LTV and proxies for job loss (via unemployment rates) in the Home Equity PD Model.

Credit scores were determined to be another useful predictor in the Home Equity Model after surveying the literature. Elul (2009) finds that low credit scores have a greater impact on subprime, low-documentation delinquency rates than they do on similar full-documentation loans.[294] The score generally reflects the overall credit performance of a borrower— if a borrower becomes past due on any of their loan obligations or becomes credit constrained, this is reflected in their credit score, which allows banks to differentiate borrowers of different creditworthiness and is a strong indicator of future default. Krainer and Laderman (2011) find that borrowers with low credit scores experienced a relatively larger increase in first-lien mortgage defaults during the financial crisis period. Overall, these results confirm the importance of debt burden, equity position, income uncertainty, and credit scores in assessing the risk of first-lien mortgage and home equity defaults.

Interestingly, a number of published papers have identified that while borrowers with higher origination credit scores are less likely to default, they are more likely to default conditional on becoming delinquent; in other words, higher credit score borrowers have lower cure rates than lower credit score borrowers. See, for example, Adelino et al. (2013). Liu and Tien (2018) find that subprime borrowers with underwater fixed-rate mortgages have higher cure rates, although the same is not found for adjustable-rate mortgages (ARMs). The aforementioned model used by the Department of Housing and Urban Development shows cure rates are lower for high and low credit score borrowers compared to borrowers with middling scores; the 2024 actuarial review (ITDC, 2023–2024) indicates that cure rates are highest for borrowers with credit scores around 660. While these findings are notable, they do not align with observed trends in the Home Equity Data, which indicates that higher credit score

[294] *See* FR Y-14M, Schedule A.1, Line Item 10 for one definition of “full-documentation” and “low-documentation” loans.

borrowers are less likely to default and, for HELOCs, more likely to cure (as indicated by the coefficients in Table D3 and Table D4). This difference might be due to different incentives for junior lien and HELOC borrowers compared to the first lien borrowers on which the aforementioned publications rely.

While these variables are of particular focus in the literature, many other variables are noted as relevant in determining home equity default. Discussion of all such variables is available in this Section D.ii.a.(2) (for variables included in the model) and Section D.ii.a.(4) (for variables considered but ultimately not included in the model).

While most of the mortgage literature focuses on first liens, a few studies have explored the outcomes of borrowers with subordinate liens, who make up most of the exposures modeled by the Home Equity Model.[295] Mayer, Pence, and Sherlund (2009)[296] find that borrowers with piggyback second liens tend to default at a higher rate after controlling for combined LTV. Calem and Sarama (2017)[297] find that borrowers with multiple liens sometimes continue to make payments on one lien while defaulting on the other and build a framework for explaining which types of borrowers exhibit this behavior. One explanation for the default decisions comes from Jagtiani and Lang (2011), who find that borrowers with larger first-lien mortgage monthly payments are more likely to default on their first-lien mortgage loans, while keeping their second-lien mortgages current.

Two papers published after the 2008 financial crisis on subordinate-lien mortgage default explore the role of HELOCs reaching the end of the draw period (end-of-draw, or EOD) in

[295] HELOCs can be either first lien products or subordinate lien products; first lien HELOCs make up a minority, albeit a substantial one, of HELOC exposures reported on FR Y-14M, Schedule B (Home Equity). The Board defines HELs based on their junior lien status, so all HELs are junior (or subordinate) lien.
[296] Mayer, C., K. Pence, and S. Sherlund 2009. "The Rise in Mortgage Defaults," Journal of Economic Perspectives, 23(1): 27-50.
[297] Calem, P.S. and Sarama, R.F., Jr. 2017. Why Mortgage Borrowers Persevere: An Explanation of First and Second Lien Performance Mismatch. Real Estate Economics, 45: 28-74.

predicting defaults (Johnson and Sarama, 2015[298]; Hall and Epouhe, 2016[299]). When loans enter EOD, the line of credit is closed and the mortgage begins to amortize, resulting in payment increases relative to the (usually) interest-only payments in place while the loan was still revolving (pre-EOD). This payment shock, which occurs simultaneously with the lost liquidity from the line closure, can put borrowers at greater risk of default—especially if the loan is structured to have a balloon payment at EOD and the borrower is unable to refinance the loan.

This, as well as other important mortgage literature, provides the basis for the development of the Home Equity PD Model. This important academic research was paired with independent analysis and review of the input data to determine the appropriate model for use in the supervisory stress test.

Support for Model Design

The Home Equity PD Model uses a loan-level, state transition model approach in which loans are defined in each period into one of four possible states and the equations in the model are used to indicate the probability of a loan in one state transitioning to another state. The loan-level framework allows for a bottom-up approach in which the individual characteristics of the loan are used to project the probability of default and payoff. This approach produces more accurate and granular projections compared to a top-down approach that relies on portfolio-level (rather than loan-level) characteristics. Given the use of a loan-level approach, a transition model is appropriate to account for the fact that default is a multi-stage process. To reach default, a borrower must fall into delinquency and then, from there, may default or may return to current status by receiving a loan modification or self-curing the delinquency. As noted in the

[298] Johnson, K.W., and R.F. Sarama 2015. "End of the Line: Behavior of HELOC Borrowers Facing Payment Changes," Finance and Economics Discussion Series 2015-073. Board of Governors of the Federal Reserve System.
[299] Epouhe, Onesime & Hall, Arden, 2016. "Payment shock in HELOCs at the end of the draw period," Journal of Economics and Business, Elsevier, vol. 84(C), pages 131-147.

review of the literature, the transition model is common throughout academic literature as well as in use by industry and government. While other model structures, such as a hazard model, can estimate default and prepayment risk at the loan level, the transition model's ability to capture the flows between intermediate and final states during the projection period make it particularly well-suited for use in the stress testing context.

The home equity model projects losses on both closed-end, junior lien home equity loans, or HELs, and home equity lines of credit (or HELOCs), which are open-ended, revolving loans.[300] The framework for modeling these products is identical, reflecting similarities between HELs and HELOCs. In particular, both HELs and HELOCs serve as a means for homeowners to access their home equity. HELs and HELOCs are reported on the same schedule on the FR Y-14M report, meaning that the variables available for use in modeling are generally the same. However, while the modeling framework is the same, HELs and HELOCs are modeled in separate equations, due to fundamental differences between the products. Notably, HELOCs are open-ended, revolving loans; borrowers can draw on their line of credit over a period of time (the "draw period") and generally make interest-only payments during this period. Meanwhile, HELs are closed-end loans with a fixed repayment schedule. Due to these differences, the exact loan, borrower, and macroeconomic characteristics that are predictive of default can vary between the products. The variables used in each transition equation are explained in detail in "Support for Variables and Transformations Included in the Model"; however, to illustrate the differences between the products some examples are provided here:

- HELOCs reported on FR Y-14M, Schedule B (Home Equity) are generally variable rate products, while HELs reported on this schedule tend to be fixed rate products. As a result, HELOCs are more sensitive to short-term interest rates (for instance, the prime

[300] HELOCs can be either first liens or junior liens. All closed-end first lien loans secured by residential real estate are modeled in the supervisory stress test by the First Lien Model.

rate), while HELs are more sensitive to long-term interest rates (for instance, the 10-year yield).

- A key predictor of default for HELOCs is utilization, or the share of the available credit that has been drawn by the borrower. Higher utilization indicates that the borrower may be liquidity-constrained and have difficulty making payments. Since HELs are closed-end products rather than lines of credit, there is by construction no available undrawn balance; therefore, utilization is not a meaningful characteristic for HELs.
- HELOCs generally have a fixed draw period over which borrowers can access the credit line and make additional draws. During this draw period, typically only interest payments are required. At the end of the draw period, no additional draws can be made, and there is generally a payment shock as the borrower becomes contractually obligated to start making principal payments. The end of the draw period is associated with both higher default and payoff rates. Default increases arise from the payment shock, as borrowers become contractually obligated to make principal payments, increasing their required payments. Payoff increases are due to the closure of the line, as borrowers often choose at this point to fully repay their principal.

The four payment statuses used in the model are defined consistent with industry definitions and are designed to be reflective of the most economically important features of loan performance. The model defines a loan as in default as if it is more than 180 days past due, or if certain other conditions are triggered. The 180-day threshold is intended to be consistent with the Federal Financial Institutions Examination Council (FFIEC) Uniform Retail Credit Classification and Account Management Policy,[301] which states the following: “For open- and closed-end loans secured by one-to four-family residential real estate, a current assessment of value should be made no later than 180 days past due, and any outstanding loan balance in excess of the value of the property, less cost to sell, should be charged off.” The other default conditions used in the model are met if the underlying collateral has been repossessed or if the loan is marked as prepaid with an associated charge-off (see Section D.ii.a.(1) for further detail). These conditions evidence that the loan was terminated and not repaid in full. Once the loan is

[301] *See* Federal Financial Institutions Examination Council. Uniform Retail Credit Classification and Account Management Policy, (June 12, 2000), https://www.federalregister.gov/documents/2000/06/12/00-14704/uniform-retail-credit-classification-and-account-management-policy.

marked as paid off with loss or the collateral is repossessed, the chance for the borrower to cure the delinquency has passed, regardless of the number of days delinquent.

The model defines loans as delinquent if they are 90–179 days past due, or in foreclosure proceedings. This is consistent with other applications that treat a loan that is three or more months behind on payments as seriously delinquent.[302] Loans in foreclosure are marked as delinquent to reflect that the loan is sufficiently delinquent for the lender to begin foreclosure proceedings.

Loans are treated as defaulted if they meet the default criteria in any month within a quarter. Similarly, loans are treated as delinquent if they meet the delinquency criteria in any month in the quarter, unless they meet the default criteria or were paid off during that same quarter. This is consistent with the principle of conservatism from the Stress Testing Policy Statement, as it ensures that delinquencies and defaults, respectively, are accounted for even if the conditions are only triggered at an intermediate point during the quarter.

The model defines loans as paid off if a loan has been paid off in full by the borrower and none of the criteria for default are triggered (in particular, no charge-off is reported).

Finally, the model defines loans as current if they are not paid off and do not meet the definitions of default or delinquent. In practice, this means that active loans with positive balances that are less than 90 days past due and not in foreclosure proceedings are treated as current.

The definitions of current and delinquent in the model are relatively broad; these broad definitions simplify the modeling approach by not treating early-stage delinquency (30–89 days

[302] For example, *see* "Household Debt Balances Continue Steady Increase; Delinquency Transition Rates Remain Elevated for Auto and Credit Cards," Federal Reserve Bank of New York, (13 Feb. 2025), https://www.newyorkfed.org/newsevents/news/research/2025/20250213.

past due) loans differently from loans that have not missed any payments, and by treating all severe delinquencies (90–179 days past due) similarly. While this assumption inhibits the model's ability to differentiate the riskiness of loans based on a more granular definition of delinquency status, it simplifies the modeling approach by limiting the number of states and transition equations in the model. Using these definitions is also consistent with the quarterly macroeconomic scenario data applied to the model to produce loss rates in the supervisory stress test, as 90 and 180 days are associated with the elapse of one and two quarters, respectively.

The model calculates the probability of loans transitioning between many of the aforementioned states. In particular, the model allows current loans to remain current or transition to the delinquent or payoff states, while delinquent loans can remain delinquent or transition to current, payoff, or default status. A key assumption implicit in the model structure is that certain transitions are not possible, as described below:

- Current loans cannot directly transition to default. This is a natural result of the model's definition of current loans as less than 90 days past due, and defaulted loans as greater than 180 days past due. Due to these definitions, the model assumes two quarters are needed for a loan to transition from current to delinquent to default. In rare circumstances in the estimation data in which loans transition directly from current to default (for instance, if the loan was liquidated or prepaid with loss prior to reaching 180 days of delinquency), such observations are removed from the estimation sample and ignored.
- Default and payoff are considered to be "terminal" states in the model; loans are not able to transition from these states to other states. In the case of payoff, this is straightforward, as once the loan has been paid off, the loan is no longer active and has no balance; a loan reported to be paid off in one quarter and then a different status in the next quarter would be presumed to be a data error. In the case of default, the model does not allow loans that have reached 180 days past due to cure and return to a different status. While cures from 180 or more days past due are observed in the historical data, they are rare, affecting less than five percent of defaulted loans, as it is uncommon for borrowers who have reached such a severe stage of delinquency to return to making regular payments. Additionally, not allowing for default cures removes the need to estimate an additional transition equation in the model. An additional equation would increase the complexity of the model and would be challenging to fit given how infrequent cures are in the historical data, potentially leading to an imprecise estimate. Finally, treating default as a terminal status is aligned with the principle of conservatism

> from the Stress Testing Policy Statement. While allowing loans to cure from default would reduce the probability of default—and therefore losses—on home equity exposures, this could lead to inappropriately low loss projections if, as is likely, fewer loans cure during a period of housing market stress. Given the challenges projecting cures from 180 or more days past due, to align with the Stress Testing Policy Statement principles and in line with the FFIEC Uniform Retail Credit Classification and Account Management Policy—which requires lenders to charge-off projected losses at least by this point—default is treated as a terminal state in the model.

The system of equations used in the model produces the probability that a loan in a given state transitions to a different state over a given quarter. Once a loan reaches a terminal state, it is assumed to remain in that state through any future periods projected by the model.

Since default is treated as a terminal state in the model, loans that enter the projection period in defaulted status are not run through the equation framework. Instead, their balances are tracked separately and losses on defaulted loans are assumed to be spread evenly across the first six projection quarters, as described further in Section D.ii.d. Spreading losses on loans starting in default over six quarters avoids the loans from all being charged off at once at the start of the projection period, which would create unreasonably high provision estimates. The choice of six quarters balances the principle of conservatism, which suggests that defaulted loans should be charged off expeditiously, with reasonableness.

Support for Variables and Transformations Included in the Model

To ensure the model is appropriately sensitive to the different indicators of default risk, the Board considered a wide range of variables for inclusion, covering characteristics of the loan and the borrower as well as macroeconomic conditions. Loan and borrower characteristics are sourced from the Home Equity Data to produce the model parameters and coefficients and from the FR Y-14M report to produce PD projections. Macroeconomic conditions are included, as described in this model description. From this wide range of variables, the final variables included in each of the 10 transition equations are chosen based on the Board's assessment of economic support, statistical fit, and, in certain cases, data availability.[303]

The variables included in each transition equation, and across equations of each product type, are chosen independently. While, in many cases, different characteristics across product type and across different transitions within a given product type justify the inclusion of different variables, the Board seeks consistency where possible. This is consistent with the stress testing principle of consistency and improves the interpretability of the model as it reduces the number of defined variables. It also simplifies the data cleaning and processing needed to run the model, as the number of terms that must be defined is minimized.

Economic support and statistical fit are used to select many of the variables included in the model. To establish economic support, the Board qualitatively assesses, based on the survey of economic literature earlier in this section and expert judgment, the most important drivers of transitions in the model. Relying on these factors to determine the set of variables considered for inclusion limits the risk of over-fitting, which could lead to inaccurate projections. The Board uses qualitative assessment to predict the relationship between a given input variable and outcome variable (in this case, the probability of a loan transitioning to a different state). With that determined, a model is estimated, and the Board uses the model estimates to determine whether the sign of the coefficient on the variable is consistent with predictions. For instance, higher credit score is associated with lower odds of nonpayment, so the coefficient on credit score in the current-to-delinquent transition should be negative. If the sign of the variable in the resulting equation does not align with expectations, the Board conducts further investigation.

[303] Because the Home Equity Data are used to produce the model parameters, variables used in the model are limited to those that can be observed in that dataset as well as the FR Y-14M. *See* Section D.ii.a.(4) for further discussion of limitations on the choices of variables necessitated by data availability. Generally, the Board has assessed that the Home Equity Data contain sufficient coverage of important variables for use in modeling.

Additionally, if a coefficient does have the expected sign but does not have an empirically important relationship with the outcome variable, the Board may exclude the variable from an equation to reduce model complexity in line with the stress test principle of simplicity.

Statistical fit is assessed based on tests of statistical significance and in-sample and out-of-sample fit. The Board tests for statistical significance via standard statistical tests and then uses measures of in-sample and out-of-sample fit further bolster statistical fit. The Board assesses in-sample and out-of-sample fit by using the model estimates to project each transition probability and then assessing whether these projected probabilities are reasonably comparable to actual probabilities. For instance, if a certain portion of loans or loans in a particular macroeconomic environment are consistently assigned projected probabilities substantially above or below their actual probabilities, this would suggest that a variable is missing or poorly specified and an adjustment to the model specification could improve the quality of the model. Consistent with the Stress Testing Policy Statement's discussion of the importance of evaluating the impact of severe economic stress, the Board pays particular attention to situations in which the specification appears to produce inaccurate projections for loans in periods of severe economic stress, such as during the 2008 financial crisis.

Variables with an interpretable economic relationship with the likelihood of a given transition that enter the relevant equation with an appropriate sign, statistical significance, and sufficient magnitude to be considered economically important are included in the final model. The statistical case for including a variable is bolstered if its inclusion meaningfully improves the ability of the model to predict outcomes for a certain subset of loans.

For the transition equations for which the sample size is larger, such as the current-to-delinquent and current-to-prepay equations, the large number of observations allows for the inclusion of more terms in the model while maintaining economic support and statistical fit in all cases. In sparser transition equations, including the transitions from delinquent, it is more difficult to support the inclusion of additional terms; as a result, many fewer variables are included in these equations.

Additional factors are considered as well. The Board considers implementation feasibility, as the variables included in the model must be projected over the 13-quarter period used to produce estimates of loan losses and allowances. The Board also considers simplicity, to retain consistency with the Stress Testing Policy Statement and to limit the Board's operational burden. If a more complex specification of the model (for instance, one with more variables) has a minimal impact on model performance compared to a simpler specification, the simpler specification is used. Finally, for situations in which the aforementioned factors of economic support, statistical fit, and implementation feasibility do not clearly point to a single option, the Board evaluates the available specifications in light of the stress testing principle of conservatism.

Certain variables in the model use linear splines to account for non-linear effects. These non-linear effects are set at discrete locations, known as "knots," as described in Section D.ii.a.(1). These knots are identified based on Board experience and expertise, including industry knowledge and review of literature; the Board selects final knots for individual variables in individual equations based on statistical fit.

Due to the fact that HELOCs are open-end, revolving products that tend to have variable interest rates, the borrower incentives involved are more complex compared to HELs. Additionally, the HELOC market is larger than the HEL market, yielding a larger estimation sample; the HELOC market was consistently more than twice as large as the HEL market in the data during the period used to estimate the model, and disparities became more pronounced during the recovery and growth period following the 2008 financial crisis period. For these reasons, the HELOC equations tend to include a larger number of variables compared to the HEL equations.

Throughout the HELOC transitions in the model, utilization is defined as the current principal balance divided by the original credit limit. Given this definition, the model depends on the share of the original available credit that has been drawn. An alternative way to define utilization is based on the current credit limit; in other words, the share of the currently available credit that has been drawn. Using the current credit limit would allow the Board to better account for how much additional credit could be drawn from the line at a given point. However, the original credit limit has advantages for supervisory stress test modeling. In particular, current credit limit is sometimes adjusted downward when a borrower has payment difficulties; this can cause mechanically high utilizations that are the effect, rather than the cause, of the borrower becoming delinquent. In the historical Home Equity Data and FR Y-14M data, these mechanical adjustments appear to be made selectively, especially after the end of the draw period, when the line is closed, limiting the comparability of the data. For instance, if a borrower who has reached the end of the draw period has 10 percent utilization and then misses a payment, and the lender responds by dropping the credit limit to the drawn balance (preventing additional draws), utilization based on original credit limit would remain at 10 percent, while utilization based on current credit limit would increase to 100 percent. This increase is not reflective of changes in the riskiness of the loan, as the loan has reached the end of the draw period and will not allow for future draws. The Board has assessed, based on historical FR Y-14M data, that this reported change does not appear to be made consistently across firms, even in cases in which the terms available to the borrower are in practice identical. Therefore, for consistency and comparability across observations, the Board uses the original credit limit to provide a more consistent representation of utilization. Generally, HELOC credit limits remain stable over time, so these disparities between original and current credit limits are uncommon.

The rest of this section discusses how the Board applies the above principles to create each of the individual transition equations. A further discussion of alternative variables not included in the model is available in Section D.ii.a.(4). For each of the variables, the variable and the interpretation of the variable's impact based on its coefficient in Tables D1 and D4 are described. In cases in which the analysis of the coefficients is supported by literature or supplementary analysis, this additional support is described as well.

HELOC, Current-to-Delinquent

- Months on book, capped at 12: Analysis of historical Home Equity Data shows that loans are less likely to transition to delinquent immediately after origination; after 12 months, the impact tends to plateau.
- Previous delinquency: Prior delinquency increases the likelihood of future delinquency, as demonstrated by the positive coefficient on this variable.
- Origination credit score (knot at 680): As credit score increases, the likelihood of delinquency falls, as observed in Krainer and Laderman (2011). Board analysis of Home Equity Data shows that this effect is non-linear; risks of becoming delinquent decrease faster for credit scores above 680, as demonstrated by the negative coefficient on the knot at 680 variable in this equation.
- Wholesale broker flag: When the loan is originated through a wholesale channel (through a broker), the lender has less direct control over the underwriting. As demonstrated by the positive coefficient on this variable, this leads to a higher risk of the borrower becoming delinquent.
- Purchase flag: This field identifies loans that are originated for the purposes of a home purchase, as opposed to loans made for other purposes such as refinance, debt consolidation, or home improvement.[304] The negative coefficient on the purchase flag variable indicates that loans originated for purchase are associated with a lower risk of delinquency than loans made for other purposes.
- Spread at origination: Spread at origination is defined as the origination interest rate minus the market reference rate reported for the loan in FR Y-14M, Schedule B.1, Line 29 (ARM Index). This reference rate is most commonly the prime rate for HELOCs. A

[304] *See* FR Y-14M, Schedule B.1 (Home Equity – Loan Level), Line Item 20 ("Loan Purpose Coding") for a full list.

higher spread at origination likely indicates that the lender believes the borrower is riskier. Accounting for spread at origination allows the model to account for characteristics not otherwise included in the model.

- First lien flag: The coefficient on this variable indicates that first liens are more likely to become delinquent than junior liens. This may appear counterintuitive, given the seniority of first liens; however, note that the model is controlling for CLTV and other features, so this variable in practice accounts for the difference in risk between a first lien loan and a junior lien loan with the same CLTV (and other features, such as loan size). Based on Board analysis of Home Equity Data, this finding is attributable to the higher default rates among first lien HELOCs that have CLTVs below 80 percent. In these cases, the presence of a junior lien implies that the borrower may have the ability to mismatch performance[305] (see Calem and Sarama, 2017) and often may choose to stay current on their junior lien rather than their first lien.
- Vintage (2006 and 2007): Loans originated in 2006 and 2007 were underwritten during the "bubble" period and tend to be riskier than other loans in ways not captured by observable variables, as demonstrated by the positive coefficient on this variable. The inclusion of this term enables the model to treat loans originated in these years as riskier than other loans with the same characteristics.
- Updated CLTV (knot at 60 and 130): This is a key determinant of delinquency in the model, consistent with the review of literature earlier in this section. Updated CLTV is calculated as origination CLTV multiplied by the house price level at origination divided by the current house price level. Accounting for the change in house prices from origination accounts for the fact that borrowers are sensitive to broad increases (or decreases) in home values. A higher CLTV indicates that the borrower has less equity in their home, limiting their incentive to make on-time payments. The Board assessed the Home Equity Data and FR Y-14M data to determine at which values of updated CLTV the risk of delinquency is most sensitive to this variable. Below 60 percent, CLTV is not meaningful, and above 130 percent, the marginal impact of increases to CLTV are small. In between these levels, increases in CLTV substantially increase the likelihood of becoming delinquent. Note that origination CLTV is based on the credit limit at origination, rather than the drawn amount; therefore, CLTV will not vary based on draws taken by borrowers after origination.
- Change in prime rate from origination through the prior quarter: Changes in the prime rate directly affect HELOC incentives by increasing interest payments, which would be expected to increase the risk of nonpayment. However, these changes also indirectly affect HELOC incentives, as prime rate changes are usually driven by broader macroeconomic trends. A sharp decline in the prime rate is associated with cuts to interest rates during a recession, which increases the risk of delinquency. Empirically, the indirect effect dominates; increases in the prime rate are associated with lower delinquency rates, as demonstrated by the negative coefficient on this variable.
- Year-over-year percentage point change in unemployment rate: Academic literature, such as Elul et al. (2010), demonstrates the importance of "double trigger" in predicting mortgage delinquency. The double trigger refers to the joint shocks to home equity

[305] "Mismatched performance" refers to a situation where at least one loan secured by a property is delinquent while one or more loans on the same property remain current.

(driven by falling home prices) and liquidity (driven by income loss); both factors are often needed to cause default. The change in unemployment rate proxies for the liquidity shock: while the model does not observe individual income levels, increases to state-level unemployment rate are predictive of income loss among borrowers in that state. Increases in unemployment rate are associated with increased delinquency, as observed in the coefficient on this variable.

- Year-over-year percent change in house price index (HPI): House price index is a measure of the level of house prices. Increases in HPI reflect appreciation, while decreases in HPI reflect house price decline.[306] House price changes are the other portion of the double trigger described in the previous bullet. House prices enter the equation both directly through this term as well as via the updated CLTV calculation. Empirically, as shown in Table D1, year-over-year decreases are predictive of delinquency.
- Utilization (knot at 85 and 100): Board analysis of Home Equity Data demonstrates that borrowers using more of their available credit lines are more likely to become delinquent. This is because higher utilization levels are suggestive of liquidity constraints, which are associated with missed payments. This impact accelerates when utilization is above 85 percent, as borrowers' available credit becomes minimal. Above 100 percent, further increases in utilization have a smaller associated increase in delinquency.
- End-of-draw variables: The model includes indicators for the quarter of end-of-draw, one quarter after end-of-draw, two quarters after end of draw, and more than two quarters after end-of-draw. Once the draw period ends, HELOCs generally convert to an amortizing loan, increasing the required payment. This payment shock is highly predictive of an increase in delinquency, as observed in Johnson and Sarama (2015) and independently confirmed by the coefficients on these variables. This risk is maximized one quarter after end-of-draw, before declining slightly (but remaining well elevated compared to prior to end-of-draw).
- Balloon payment flag: Certain HELOCs have terms that require a balloon payment of the entire outstanding balance at end-of-draw. This payment shock makes it much likelier for loans with balloon payments to transition to delinquency.
- Seasonality: Higher delinquency is observed in the Home Equity Data in the third and fourth quarters of the year compared to the first two quarters, reflecting that household balance sheets are predictably cyclical.

HELOC, Current-to-Payoff

- Months on book, capped at 24: Analysis of the Home Equity Data shows that prepayment rates increase as loans become more seasoned; this effect tends to plateau after two years.
- Origination credit score (knot at 720): As observed by the coefficients in this equation, payoff rates tend to increase as credit scores increase for borrowers with credit scores less than 720; above this level, payoff rates decrease as credit scores increase.
- Original loan size: The coefficient on origination loan size is negative in this equation, suggesting that larger loan sizes somewhat decrease the likelihood of prepayment.
- Flag for 2007, 2008, and post-2010 observations: The Home Equity Data reveals that payoff rates were systematically lower in 2007, 2008, and after 2010 compared to the

[306] *See* Section D.ii.a.(3) for details on the assignment of house price index to each loan.

pre-crisis levels. The historical Home Equity Data does not show these observably lower payoff rates in 2009, and Board analysis indicates there may have been reporting irregularities during this year.[307] Instead, the model treats observations in 2009 as if they will pay off at the equivalent rate as pre-2007 observations. As the projection periods in supervisory stress tests occur after 2010, the post-2010 flag is applied to all observations when producing model projections.

- Wholesale broker flag: Loans originated through wholesale channels are more likely to pay off, as indicated by the positive coefficient on this variable. In general, loans originated through wholesale brokers exhibit different characteristics, as the lender has less direct control over the loan underwriting.
- Purchase flag: Loans originated for purchase are associated with a lower likelihood of prepayment, as indicated by the negative coefficient on this variable.
- First lien flag: First liens are less likely to prepay than junior lien HELOCs, as indicated by the negative coefficient on this variable.
- Updated CLTV (knot at 60): Borrowers with less equity tend to be less likely to pay off the loan; this trend is observed in the Home Equity Data. Board analysis of Home Equity Data indicates that these impacts are concentrated in loans with updated CLTV above 60 percent; based on this finding, the model does not consider changes in updated CLTV below 60 percent.
- Change in prime rate from origination through the prior quarter: Changes in the prime rate directly affect HELOC incentives by increasing interest payments, which would be expected to increase the likelihood of prepayment as it reduces incentives to borrow. However, these changes also indirectly affect HELOC incentives, as prime rate changes are usually driven by broader macroeconomic trends. A sharp decline in the prime rate is associated with cuts to interest rates during a recession, which reduce mortgage market activity, including prepayment. Empirically, the indirect effect dominates; increases in the prime rate are associated with higher payoff rates, as demonstrated by the positive coefficient on this variable.
- Spread of 10-year Treasury rate over 3-month Treasury rate in the prior quarter: A lower spread indicates weaker economic expectations; as a result, prepayment is less likely. This theoretical relationship is confirmed by the model results, which show a negative coefficient on this variable. Borrowers expecting weaker economic conditions will prioritize maintaining access to liquidity.
- Year-over-year percent change in HPI: Borrowers tend to be more likely to pay off their loans in appreciating housing markets, as observed by the positive coefficient on this variable.
- Utilization (knots at 10, 95, and 100): The Board reviewed the likelihood of prepayment for borrowers with different utilization rates and determined that the impact of utilization on prepayment varies widely across the range of values. At extremely low utilization rates (less than 10 percent), increases in utilization tend to reduce prepayment, as borrowers are less likely to prepay as their balances become non-trivial. Above 10 percent, this trend reverses, and prepayment is slightly more likely as utilization

[307] The Board tested applying a treatment accounting for such irregularities and found that the impacts on other coefficients or on loss projections were small enough that they would not notably impact results; therefore, in line with the stress testing principle of simplicity, no adjustment is made to the input data.

increases. Between 95–100 percent utilization, increases tend to more substantially increase prepayment probability, as borrowers are incentivized to refinance their HELOCs into other forms of debt. Above 100 percent, the impact is small; utilization above 100 percent is rare. See the coefficients on these variables for evidence of these trends.

- End-of-draw variables: Loans are substantially more likely to pay off starting five quarters before end-of-draw, with the effect at its peak in the quarter before end-of-draw. This is observed in Hall and Epouhe (2016) and independently confirmed by the coefficients on these variables. At end-of-draw, borrowers have less incentive to keep their HELOC on the book, as they no longer have access to the credit line.
- Balloon payment flag: Payoff tends to be likelier among loans with a balloon payment, as the balloon payment requires borrowers to make a large, one-time payment at the end of a loan-term. This is evidenced by the positive coefficient on this variable.
- Seasonality: Payoff rates are higher in the first two quarters of the year, as observed in the historical Home Equity Data, reflecting that household balance sheets are predictably cyclical.

HELOC, Delinquent-to-Current

- Previous delinquency: Loans that have remained in the delinquent state for multiple quarters are more likely to cure (return to current) than loans that have recently entered delinquency, as observed by the positive coefficient on this variable. Remaining in delinquency reveals that borrower has made payments since becoming delinquent, possibly signaling an intent to self-cure.
- Spread at origination: The negative coefficient on this variable indicates that loans with higher spreads at origination are less likely to cure, likely reflecting the increased riskiness of these loans.
- Updated CLTV (knot at 60): As demonstrated in the review of literature above in this section, the borrower's level of equity in the home is highly predictive of their likelihood of defaulting. The coefficients confirm that this effect extends to the likelihood of curing from delinquency as well. Board analysis of the Home Equity Data for the likelihood of curing for borrowers with varying updated CLTVs shows that this impact is concentrated for CLTVs above 60 percent, as borrowers have less home equity to recover in these cases; therefore, the model considers the impacts of CLTV only above 60 percent.
- Origination credit score (knot at 720): Below 720, no credit score impact is observed in the historical Home Equity Data. For loans to borrowers with credit scores above 720, historically, a higher origination credit score is associated with a slightly higher likelihood of curing.
- High utilization flag: The negative coefficient on this variable indicates that highly utilized lines (over 90 percent) are less likely to cure, as high utilization indicates that the borrower is liquidity constrained. This is specified as a flag rather than a continuous variable as it reflects broadly different behavior between high and low utilization borrowers; because the observed relationship in the Home Equity Data between utilization and the likelihood of becoming current is hard to predict, the Board has

determined that a flag produces more reasonable results compared to a continuous specification.

HELOC, Delinquent-to-Payoff

- Months on book (Capped at 240): Loans that are more seasoned tend to be less likely to pay off than newly originated loans, as observed by the negative coefficient on this variable.
- Previous delinquency: The negative coefficient on this variable indicates that loans that have been in the delinquent state for multiple consecutive quarters are less likely to pay off, as borrowers who are able to pay their full balance down generally do so as soon as they enter delinquency.
- Origination credit score: The positive coefficient on this variable indicates that borrowers with higher origination credit scores are more likely to pay off their delinquent loans, potentially reflecting greater access to outside sources of credit.
- Original loan size: This variable enters this equation with a negative coefficient, indicating that larger HELOCs are less likely to pay off from delinquency.
- Updated CLTV (knots at 80 and 105): The Board reviewed the relationship between updated CLTV and payoff for delinquent loans in the Home Equity Data to determine the model specification. CLTVs below 80 percent have a negligible impact on payoff, but as updated CLTV increases above that level, payoff is more likely, as borrowers attempt to exit their position without defaulting. Once the borrower tips into negative equity territory (above 105 percent), this estimated marginal impact is smaller, as borrowers with negative equity tend to have a lower ability to avoid default with no equity. The coefficients on these variables confirm these findings.
- First lien flag: The negative coefficient on this variable indicates that first liens are less likely to pay off from delinquency.
- End-of-draw variables: The negative coefficients on the end-of-draw variables indicate that payoff is less likely for delinquent loans within 5 quarters of (or following) end-of-draw.
- Seasonality: The coefficients on these terms indicate that loans are more likely to pay off in the third quarter, and less likely to pay off in the fourth quarter, compared to the first two quarters of the calendar year, reflecting that household balance sheets are seasonal.
- Flag for 2007, 2008, 2009, and post-2010 observations: The historical Home Equity Data show that loans are more likely to prepay from delinquent status in 2007, 2008, and after 2010 than in earlier years, reflecting a regime change following the onset of the 2008 financial crisis. The year 2009 is an exception to this trend, as prepayment rates were generally lower in this year compared to other years. See the coefficients for the exact magnitudes of impacts. As the projection periods in supervisory stress tests occur after 2010, the post-2010 flag is applied to all observations when producing model projections.
- Change in yield on 10-year Treasury from origination: Increases in the 10-year Treasury rate from origination likely indicate improved economic expectations and tend to encourage payoff, as indicated by the positive coefficient on this variable. This is despite the fact that higher interest rates increase the cost of refinancing.

HELOC, Delinquent-to-Default

- Months on book: The negative coefficient on this variable indicates that delinquent loans are less likely to transition to default as they become more seasoned.
- Previous delinquency: Loans that have remained in the delinquent state for multiple quarters are less likely to proceed to default than loans that recently entered delinquency, as observed by the negative coefficient on this variable. Loans remaining in delinquent state indicate that borrower has made payments since becoming delinquent, possibly signaling an intent to self-cure.
- Origination credit score: The positive coefficient on this variable indicates that borrowers with higher credit scores tend to be more likely to proceed to default once they reach delinquency. While lower credit score borrowers are more likely to fall in and out of delinquency, the model outputs suggest that higher credit scores are associated with proceeding to default.
- Original loan size: Larger loans empirically show a slightly lower risk of default given delinquency compared to smaller loans, as observed by the negative coefficient on this variable.
- Purchase flag: Loans originated for purchases are empirically more likely to proceed to default upon reaching delinquency, as observed by the positive coefficient on this variable.
- Spread at origination: Loans with higher spreads at origination tend to be less likely to proceed to default historically, as observed by the negative coefficient on this variable. Once reaching delinquent status, the general connection between higher spreads and higher risks appears to reverse, potentially because borrowers with loans with higher spreads are more willing to remain in intermediate states of delinquency.
- First lien flag: Delinquent first lien HELOCs are more likely to default compared to junior liens, as observed by the positive coefficient on this variable. This may appear counterintuitive, given the seniority of first liens; however, note that the model is controlling for CLTV and other features, so this variable in practice accounts for the difference in risk between a first lien loan and a junior lien loan with the same CLTV (and other features, such as loan size). Based on Board analysis of Home Equity Data, this finding is attributable to the higher default rates among first lien HELOCs that have CLTVs below 80 percent. In these cases, the presence of a junior lien implies that the borrower may have the ability to mismatch performance (see Calem and Sarama, 2017) and often may choose to stay current on their junior lien rather than their first lien.
- Updated CLTV (knot at 60): As demonstrated in the review of literature above in this section, the borrower's level of equity in the home is highly predictive of their likelihood of defaulting. The coefficients confirm that this effect extends to proceeding to default from delinquency. Board analysis of the Home Equity Data for the likelihood of default for delinquent borrowers with varying updated CLTV shows that this impact is concentrated for CLTVs above 60 percent, as borrowers have less home equity to recover in these cases; therefore, the model considers the impacts of CLTV only above 60 percent.
- Change in the prime rate from origination through the prior quarter: Changes in the prime rate directly affect HELOC incentives by increasing interest payments, which would be expected to increase the risk of nonpayment. However, these changes also indirectly

affect HELOC incentives, as prime rate changes are usually driven by broader macroeconomic trends. A sharp decline in the prime rate is associated with cuts to interest rates during a recession, which increases the risk of default. Empirically, as observed in the coefficients on these variables, the indirect effect appears to dominate; increases in the prime rate are associated with higher default rates in the model equations.

- Flag for 2007 and 2008 observations: During the 2008 financial crisis period (specifically, in 2007 and 2008), historical Home Equity Data show that loans were more likely to proceed to default after reaching delinquency. This is observable in the positive coefficients on these variables.
- High utilization flag: The positive coefficient on this variable indicates that highly utilized lines of credit (those with utilization above 90 percent) are more likely to default, as high utilization indicates that the borrower is liquidity constrained. This is specified as a flag rather than a continuous variable as it reflects broadly different behavior between high and low utilization borrowers; because the observed relationship in the Home Equity Data between utilization and likelihood of becoming current is hard to predict, the Board determined that a flag produces more reasonable results compared to a continuous specification.

HEL, Current-to-Delinquent

- Months on book, capped at 12: Analysis of historical Home Equity Data shows that loans are less likely to transition to delinquent immediately after origination; after 12 months the impact tends to plateau.
- Previous delinquency: Prior delinquency increases the likelihood of future delinquency, as demonstrated by the positive coefficient on this variable.
- Origination credit score (knot at 720): As credit score increases, the likelihood of delinquency falls, as observed in Krainer and Laderman (2011). Board analysis of Home Equity Data shows that this effect is non-linear; risks of becoming delinquent decrease faster for credit scores above 720, as demonstrated by the negative coefficient on the knot-at-720 variable.
- Original loan size, capped at $150,000: Empirically, larger loans are more likely to transition to delinquent, as indicated by the positive coefficient on this variable. Historical Home Equity Data show that this impact tends to phase out once loans become very large (with origination amounts above $150,000); based on this finding, the variable is capped at this level.
- Wholesale broker flag: When the loan is originated through a wholesale channel (through a broker), the lender has less direct control over the underwriting. As demonstrated by the positive coefficient on this variable, this leads to a higher risk of the borrower becoming delinquent.
- Purchase flag: Home equity loans used for purchases are historically riskier than other home equity loans. In the run-up to the 2008 financial crisis, many borrowers used "piggy-back" second lien home equity loans to make purchases while reducing the LTV of their first mortgage, as observed in, for instance, LaCour-Little, Calhoun, and Yu

(2011).[308] As a result, loans marked as being for the purpose of purchase are treated as riskier than other loans; this finding is confirmed by the positive coefficient on this variable.

- Spread at origination: Similar to HELOCs, for HELs, spread at origination is defined as the origination interest rate minus a reference rate, except that for HELs, which are typically fixed rate and therefore not contractually linked to an index, the reference rate is the 10-year Treasury yield. Board analysis of the Home Equity Data shows that the 10-year Treasury yield historically tracks HEL interest rates reasonably closely. A higher spread at origination tends to indicate that the lender believes the borrower is riskier. Accounting for spread at origination allows the model to account for characteristics not otherwise included in the model.
- Vintage (2006 and 2007): Loans originated in 2006 and 2007 were underwritten during the "bubble" period and are riskier than other loans in ways not captured by observable variables, as demonstrated by the positive coefficient on this variable. The inclusion of this term enables the model to treat loans originated in these years as riskier than other loans with the same characteristics.
- Updated CLTV (Bounded at 60 percent and 160 percent): This is a key determinant of delinquency in the model, consistent with the review of literature above in this section. Updated CLTV is calculated as origination CLTV multiplied by the house price level at origination divided by the current house price level. Incorporating the change in house prices from origination accounts for the fact that borrowers are sensitive to broad increases (or decreases) in home values. A higher CLTV indicates that the borrower has less equity in their home, limiting their incentive to make on-time payments. The Board assessed the Home Equity Data and FR Y-14M data to determine at which values of updated CLTV the risk of delinquency is most sensitive to this variable. Below 60 percent and above 160 percent, further changes to CLTV are not empirically meaningful. In between these levels, increases in CLTV substantially increase the likelihood of becoming delinquent. Note that origination CLTV is based on the loan amount at origination, rather than the current balance; therefore, CLTV will not vary as borrowers make payments on the loan. Using original loan balance simplifies the modeling process and has minimal impact on loss projections, as principal balance is generally very similar to origination loan amount in practice.
- Year-over-year percentage point change in unemployment rate: Academic literature, such as Elul et al. (2010), demonstrates the importance of the "double trigger" in predicting mortgage delinquency. The double trigger refers to the joint shocks to home equity (driven by falling home prices) and liquidity (driven by income loss); both factors are often needed to cause default. The change in unemployment rate proxies for the liquidity shock: while the model does not observe individual income levels, increases to state-level unemployment rate are predictive of income loss among borrowers in that state. Increases in unemployment rate are associated with increased delinquency, as observed in the coefficient on this variable.
- Year-over-year percent change in house price index (HPI): House price index is a measure of the level of house prices. Increases in HPI reflect appreciation, while

[308] LaCour-Little, M., C. Calhoun, and W. Yu, 2011, What Role Did Piggyback Lending Play in the Housing Bubble and Mortgage Collapse?, *Journal of Housing Economics*, 20(2): 81-100.

decreases in HPI reflect house price decline.[309] House price changes are the other portion of the double trigger described in the previous bullet. House prices enter the equation both directly in this term as well as via the updated CLTV calculation. Empirically, based on the coefficient on this variable, year-over-year declines are predictive of delinquency.

HEL, Current-to-Payoff

- Months on book, capped at 12: Analysis of the Home Equity Data shows that prepayment rates increase as the loan becomes more seasoned; this effect tends to plateau after one year.
- Origination credit score (above 720): Loans to borrowers with credit scores about 720 are empirically more likely to pay off than other loans, as observed by the positive coefficient on this variable. No significant impact is observed in the historical Home Equity Data for credit scores below 720.
- Original loan size, capped at $150,000: Empirically, as demonstrated by the positive coefficient on this variable, larger loans tend to be more likely to pay off. In the historical Home Equity Data, this impact tends to phase out once loans become very large (with origination amounts exceeding $150,000), so the variable is capped at this level.
- Flag for 2007, 2008, 2009, and post-2010 observations: The Home Equity Data reveals that payoff rates were systematically lower in 2007 compared to the pre-crisis levels, and even lower than 2007 in 2008, 2009, and after 2010. As the projection periods in supervisory stress tests occur after 2010, the post-2010 flag is applied to all observations when producing model projections.
- Wholesale broker flag: Loans originated through wholesale channels are more likely to pay off, as indicated by the positive coefficient on this variable in Table D2. In general, loans originated through wholesale brokers show different characteristics, as the lender has less direct control over the loan underwriting.
- Purchase flag: Because home equity loans used for purchases are often "piggy back" loans where the borrower is unable to get a single loan large enough to cover the purchase (see LaCour-Little, Calhoun, and Yu, 2011), refinancing options tend to be more limited for these borrowers. Empirically, this is observed via the negative coefficient in this variable.
- Updated CLTV (knots at 50, 60, 75 and 160): The Board reviewed the relationship between updated CLTV and payoff in the historical Home Equity Data to assess how the impact varied at different values of CLTV. The findings are confirmed by the coefficients observed in this equation. For updated CLTVs below 50 percent, prepayment likelihood increases as updated CLTV increases. This is likely due to the low value of refinancing for loans representing a small fraction of the property value. Between 50–75 percent, changes in updated CLTV do not meaningfully impact prepayment incentives. Above 75 percent, prepayment tends to decline as updated CLTV increases. Above 160 percent, the observed impact is small, but updated CLTV above 160 percent is in practice rare. These trends reflect that borrowers are most incentivized to prepay when they have a solid but not overwhelming equity stake in the property. Note that the model uses the previous

[309] *See* Section D.ii.a.(3) for details on the assignment of house price index to each loan.

quarter's value of CLTV, while the knots above 50 percent are based on the contemporaneous value of CLTV. Since CLTV generally changes little in a given quarter, this timing mismatch generally does not significantly impact projected prepayment. In cases in which no previous updated CLTV is observed (for the first observation of a given loan), it is assumed that the previous CLTV and the contemporaneous CLTV are identical.

- Year-over-year change in the 10-year Treasury yield: As Treasury yields fall, refinancing tends to become more attractive to borrowers; as Treasury yields rise, refinancing tends to become less attractive. This trend is reflected in this term, which enters the model with a negative coefficient.
- Change in 10-year Treasury yield from origination in prior quarter (knot at 0): The change in the yield since origination reflects refinance incentives; a 10-year Treasury yield that is lower than its origination level suggests that a borrower can refinance into a cheaper loan. As the coefficients on these variables demonstrate, this impact is stronger for decreases from origination; borrowers are less likely to pay off as the current 10-year yield increases, but this impact is more muted for increases from origination levels, as refinance incentives are negative when yields are above their origination values.

HEL, Delinquent-to-Current

- Previous delinquency: Loans that have remained in the delinquent state for multiple quarters are more likely to cure (return to current) than loans that recently entered delinquency, as observed by the positive coefficient on this variable. Loans that remain in a delinquent state reveal that borrowers have made payments since becoming delinquent, possibly signaling an intent to self-cure.
- Months on book: Seasoned loans are empirically more likely to cure than less seasoned loans, as indicated by the positive coefficient on this term.
- Updated CLTV (bounded at 60 percent and 160 percent): As demonstrated in the review of literature above in this section, the borrower's level of equity in the home is highly predictive of their likelihood of defaulting. The coefficients confirm that this effect extends to the likelihood of curing from delinquency as well. Board analysis of the Home Equity Data for the likelihood of curing for borrowers with varying updated CLTVs shows that this impact is concentrated for CLTVs above 60 percent and below 160 percent. Below 60 percent, the borrower has substantial equity and incremental changes to updated CLTV have little impact; above 160 percent, the loan amount is so much higher than the collateral value such that additional increases in updated CLTV have little impact on the borrower's decision to cure. Therefore, the model considers the impacts of CLTV in between these values.

HEL, Delinquent-to-Payoff

- Previous delinquency: The negative coefficient on this variable indicates that loans that have been in the delinquent state for multiple consecutive quarters are less likely to pay off, as borrowers that are able to pay their full balances down generally do so as soon as they enter delinquency.

- Flag for 2009 observations: Empirically, the year 2009 has fewer observed payoffs from delinquency compared to other years. This is accounted for through this term, as indicated by the negative coefficient on this variable.
- Change in 10-year Treasury yield from origination through the prior quarter: The change in the yield since origination reflects refinance incentives; lower 10-year Treasury yields (compared to origination) tend to allow borrowers to refinance into cheaper loans. This term is specified as the difference between the 10-year yield at origination and the 10-year yield in the previous quarter, so a positive value indicates that the debt would be cheaper (have a lower interest rate) after refinancing. This effect is demonstrated through the positive coefficient on this variable.

HEL, Delinquent-to-Default

- Months on book: The negative coefficient on this variable indicates that delinquent loans are less likely to transition to default as they become more seasoned.
- Previous delinquency: Loans that have remained in the delinquent state for multiple quarters are less likely to proceed to default than loans that recently entered delinquency, as observed by the negative coefficient on this variable. Loans that remain in the delinquent state reveal that borrowers have made payments since becoming delinquent, possibly signaling an intent to self-cure.
- Origination credit score: The positive coefficient on this variable indicates that borrowers with higher credit scores tend to be more likely to proceed to default once they reach delinquency. While lower credit score borrowers are more likely to fall in and out of delinquency, the model outputs suggest that higher credit scores are associated with proceeding to default.
- Purchase flag: As noted for other transition models, home equity loans used to purchase houses tend to be riskier than other loans. The positive coefficient on this variable shows that this effect is observed in this equation as well. In particular, these loans tend to be more likely to proceed to default.
- Wholesale broker flag: When the loan is originated through a wholesale channel (through a broker), the lender has less direct control over the underwriting. As indicated by the negative coefficient on this variable, this is associated with a lower likelihood of a delinquent borrower defaulting.
- Updated CLTV (bounded at 60 percent and 160 percent): As demonstrated in the review of literature above in this section, the borrower's level of equity in the home is highly predictive of their likelihood of defaulting. The coefficients confirm that this effect extends to proceeding to default from delinquency as well. Board analysis of the Home Equity Data for the likelihood of default for delinquent borrowers with varying updated CLTV shows that this impact is concentrated for CLTVs above 60 percent and below 160 percent. Below 60 percent, the borrower has substantial equity and incremental changes to updated CLTV have little impact; above 160 percent, the loan amount is so much higher than the collateral value such that additional increases in updated CLTV have little

impact on the borrower's decision to default. Therefore, the model considers the impacts of CLTV in between these values.

- Year-over-year percent change in HPI: Rising house prices tend to reduce the incentives for borrowers to proceed to default, and vice versa. This theoretical perspective is supported by the negative coefficient on this variable.
- Flag for 2010 and after observations: Empirically, as observed in the historical Home Equity Data and indicated by the positive coefficient on this variable, loans originated after 2010 are likelier to proceed to default upon becoming delinquent.

(3) Adjustments and Data Cleaning Steps

Estimation Sampling and Loan Inclusion

This section describes the sampling and filtering processes applied to the Home Equity Data to produce the model parameters.

To start, the dataset is filtered to a 20 percent sample of HELOCs and a 30 percent sample of HELs. Random sampling is used to ensure the data remain representative of the entire Home Equity Data while ensuring the size of the dataset is manageable for modeling; including more loans increases the run time and memory cost of implementing the model without substantially increasing the reliability of the results. For HELOCs, a 20 percent sample is large enough to ensure reliability; for HELs, a larger 30 percent sample is used. The larger sample for HELs is related to two factors. First, there are fewer HELs in the data compared to HELOCs, especially post-2010; a smaller sample risks leaving the data too sparse, which could lead to imprecisely estimated parameters. Second, among HELs that are included in the data, a larger share is missing key fields needed for modeling. The larger sample ensures that sufficient observations are retained after data cleaning and filtering to produce reliable model estimates.

From this sample, observations between January 2002 and December 2017 are kept. One key advantage of the Home Equity Data is that it provides coverage over a long history, including during the 2008 financial crisis period, during which there was significant stress to the housing market. The model uses a start date of January 2002 to include data prior to the housing bubble that preceded the 2008 financial crisis period, expanding the set of macroeconomic environments over which the model is trained. Using data through December 2017 ensures coverage of the model across an entire business cycle. The Board considered further extending the end date to cover more recent periods and analyzed the possibility by testing re-estimating the model incorporating data through 2022. The analysis demonstrated that the inclusion of more recent periods does not lead to substantial changes to model projections or improvements in reliability. Based on this finding, the Board determined that the end date of December 2017 is appropriate. For additional discussion of the periods used to calibrate the model, see Section D.iii.a.

Given this starting dataset, additional filters are applied to ensure the data are representative and of sufficient quality for inclusion in the model. First, only loans originated in or after January 2002 are included, and loans are excluded if more than six months elapse between the origination of the loan and the first observation date. The exclusion of pre-2002 vintages limits the ability of the model to predict transition probabilities for loans originated prior to this date; however, as loans rarely persist in the data for more than 20 years, the risk to model representativeness when applied to current data is low. On the other hand, including these filters ensures that loans are included only if the entire loan history is available. Loans that are missing observations at the beginning of their histories are problematic because they are susceptible to survivorship bias,[310] which can bias the model estimates.

[310] To understand survivorship bias, consider two loans, each of which is not reported for the first 6 months after origination. The first loan defaults in the first 6 months, while the second loan remains current during this period. Because the first loan has defaulted already, it will never be reported, while the second loan will begin to be reported after the 6 months have elapsed. Including the second loan in the estimation data would introduce bias, as loans missing observations are only included if they do not transition to default or payoff prior to appearing in the data.

Because the data was compiled over time from various servicers, critical fields are missing from many observations. To ensure reliable model estimates, loans are excluded if any of the following conditions are met, which would otherwise prevent the use of critical fields used to produce variables included in the model equations:

- Missing loan size at origination, as this variable is included in many transitions.
- Lien type (first lien, second lien, etc.) is missing, or a HEL is marked as first lien. While HELOCs can be first liens, closed-end, first lien home equity loans are modeled using the First Lien Mortgage model. Therefore, HELs marked as first liens (or missing lien types) are removed. Lien status is additionally needed for HELOCs as the term is included in certain HELOC transition equations.
- Origination credit score is missing, as this variable is used in many transitions.
- Appraisal value or property value is missing, as this variable is used to calculate certain transformations of CLTV, a key variable in many transitions.
- Origination LTV or CLTV is missing or invalid, as this variable is used in many transitions. Original CLTV is considered to be invalid in the following situations:
    - Original CLTV is the less than or the same as original LTV even though the loan is not a first lien. Since LTV is based only on the loan itself, while CLTV includes more senior liens as well and therefore a higher total loan balance used in the numerator of the LTV calculation, CLTV should be strictly higher than LTV if the loan is not a first lien.
    - Original CLTV is less than original LTV by more than 1 percent, for first liens. For first liens, original LTV and original CLTV are expected to be identical; a small difference is allowed as long as it is within a 1 percent tolerance to avoid overly filtering the data.
    - Original LTV is less than zero for loans that are not first liens. In situations in which first liens have negative LTV, the CLTV is used instead.
- Property state is missing or is not one of the 50 U.S. states or Washington, DC, as historical unemployment rates and house prices are merged in at the state and county levels. Without a valid property state, these values cannot be filled. Furthermore, in most cases, domestic home equity balances exclude loans to borrowers in U.S. territories (see FR Y-9C instructions at 391, glossary entry for “Domestic Office”); as a result, these loans are not in the scope of loans covered by the Home Equity Model, which covers domestic exposures only.

Additionally, loans are excluded if any of the following conditions are triggered, which are suggestive of data quality issues:

- Maturity date is prior to origination date.
- First payment date is prior to origination date.
- Origination date is after the first reporting period.

- Principal balance amount is negative or missing.

Furthermore, loans are excluded if the following conditions apply, which would prevent them from being included in the model's transition framework:

- The first reported observation is in default or paid off.
- A loan moves from less than 90 days past due to greater than 180 days past due in a single quarter. This is indicative of a current-to-default transition, which is not allowed by the model.

Lastly, a small number of loans (less than 0.25 percent of the total) are removed if variables exceed certain pre-defined thresholds. These loans are removed because they reflect outliers, and their inclusion in the model could negatively impact model performance for other types of loans. These thresholds are defined below:

- Original loan amount: Less than $100 or greater than $10,000,000
- Original credit limit: Less than $100 or greater than $10,000,000
- Property value at origination: Less than $10,000 or greater than $12,000,000
- Origination CLTV: Greater than 125

Together, these conditions filter a material portion of loans from the sample. Since the large share of observations removed from the data could raise concerns about representativeness, the Board compared the distribution of key variables in the final dataset such as origination credit score, origination CLTV, payment status, and loan vintage (year of origination) to that of equivalent fields in the FR Y-14M report. The analysis showed that the distribution of key fields in the FR Y-14M data are similar to that of the filtered Home Equity Data on key indicators. Given these comparisons, the filtered data used to estimate the model parameters appear to reasonably approximate the data used to project losses. Additional details regarding the choice of data are found in Section D.ii.a.(4).

Estimation Data Cleaning and Preparation

Loans that remain in the data following the filtering process described above are cleaned to prepare for inclusion in the model. Notably, while data are reported monthly, the model relies on quarterly transitions, so the monthly observations must be aggregated into quarterly data. For most dynamic variables, this is implemented by using the value reported in the last month of a quarter. Using the quarter-end observation provides a consistent definition across time. The exception to this implementation is payment status (current, late, payoff, or default). For this variable, loans are considered defaulted if a default occurs at any point in a quarter; payoff if paid off at any point in the quarter, as long as the payoff event was not associated with a default; delinquent, if observed at any point in the quarter as long as payoff or default were not separately observed; and finally, current, if none of the other statuses are observed during the quarter. This is in line with the stress testing principle of conservatism, as it ensures that delinquencies and defaults, respectively, are accounted for even if the conditions are only triggered at intermediate point during the quarter.

Next, loans with payment statuses that cannot be identified and loans that disappear from the sample in a given quarter, and that were delinquent in the previous quarter, are treated as defaulted. This generally occurs when delinquent loans are transferred to different collection systems, which can lead to the loans no longer being reported to the data vendor. The Board has determined that loans are most likely to disappear from the data when they reach default. This is evidenced by the fact that delinquent loans disappear from the Home Equity Data at a rate four times higher than the rate at which current loans disappear from the Home Equity Data. Ignoring these situations (in other words, not modeling the transition from delinquency for loans that are not observed in the following quarter) would bias downward estimates of default risk. One concern with this approach is that some loans that disappear from the data after reaching delinquency may not have defaulted; it is possible that they paid off, cured, or were sold. Given the uncertainty, the likely explanation in the majority of these cases is that they disappeared due to the removal of loans from lenders' servicing systems. Consistent with the principle of conservatism, the Board determined that treating these loans as transitioning to default is appropriate.

For HELOCs, one variable that is needed to produce model estimates is the draw period. HELOCs are more likely to transition to default or payoff states in the quarters immediately before and after the end-of-draw date; this is a key term in the HELOC PD model. However, over a quarter of HELOCs are missing information on the draw period needed to compute the end-of-draw date. To avoid further filtering of the data and avoid introducing selection bias,[311] instead of dropping these loans the model assumes loans with missing draw periods have 10-year draw periods. A 10-year draw period is chosen because this is by far the most common draw period among observations in both the Home Equity Data and FR Y-14M data for observations for which this variable was reported, accounting for a majority of such observations. The prevalence of the 10-year draw period is observed across loans with many different loan terms.

Next, macroeconomic data is merged with the Home Equity Data. The macroeconomic data is applied in the model both as of the origination date of the loan (for instance, to calculate spread at origination) as well as contemporaneously (for instance, to calculate the percent change in HPI). Data are merged at a quarterly frequency; these data correspond to the last month of a given quarter. For contemporaneous data, this is necessitated by the model's use of quarterly transitions and aligns with the frequency used in projections. For origination data, it is possible

[311] Draw period is notably missing for a large share of HELOCs with 25-year terms.

to use monthly data instead; however, the quarterly data simplifies the modeling process and allows for the maintenance of a smaller macroeconomic dataset.

Macroeconomic data used in the Home Equity Model is as follows:

- House price index, sourced from a third-party vendor.[312]
- Unemployment rate,[313] produced by the Bureau of Labor Statistics.
- U.S. prime rate, sourced from the Federal Reserve Board of Governors. See “Selected Interest Rates, H.15 Release” (Series RIFSPBLP_N.M).
- Various maturities of yields of U.S. Treasuries, sourced from the Federal Reserve Board of Governors. See “Selected Interest Rates, H.15 Release.”

For macroeconomic variables that are merged at the national level (in particular, measures of interest rates), the same macroeconomic variable value is assigned to all loans in a given quarter. Unemployment rate is merged at the state level, based on the state in which the property is located. House price index is merged at the county level when possible, based on a mapping of the reported ZIP code of the property to a county. For ZIP codes that cannot be mapped to a county, or for counties for which house price index is not provided,[314] the state-level house price index is used instead.[315] This process allows for the inclusion of house price information at the county level when available to ensure the model is reflective of true housing market conditions.

With these adjustments applied, the Board creates the model variables and uses them to produce the model parameters.

[312] The Board does not adjust the values of the house price index sourced from the vendor when estimating the model coefficients (such as by seasonally adjusting the data).
[313] The Home Equity PD Model is estimated using the seasonally adjusted unemployment rate as of the end of a given quarter.
[314] House price index is not reported for all counties. Generally, smaller counties with fewer housing transactions are less likely to have house price index available.
[315] Formally, the model uses the national value when the state-level house price index is not available; however, the state-level index is in practice always available.

Projection Data Cleaning and Preparation

The model parameters produced in this section are applied to reported data to produce projections of PD and payoff rates. As for the estimation data, several data cleaning steps are necessary to prepare the projection data for use.

First, data reported on the FR Y-14M that are not appropriate for use in model projections are removed. Such cases are as follows:

- Closed-end home equity loans reported as first liens are removed, as these loans should be reported on FR Y-14M, Schedule A.1 (First Lien). Losses on first lien HELs are projected by the First Lien model.
- Loans held for investment classified as fair value option (FVO) or held for sale (HFS) are removed, as losses for these loans are projected by the FVO model.
- Loans that are marked as having a commercial purpose are removed. Due to the way the FR Y-9C instructions and FR Y-14M instructions are written, all HELOCs and HELs secured by one-to-four family residential real estate located in the United States are included in the FR Y-14M, regardless of whether the loan is for a commercial purpose. Commercial loans have different historical behavior than non-commercial loans and are also frequently missing key fields necessary for modeling.[316] Instead, these loans are assigned losses separately using a process outlined in more detail in Section D.ii.e.
- Loans that are not marked as HELOC or HEL are removed, as they cannot be reliably run through either model.
- Loans that are securitized are removed, as these loans are not on banking organizations' portfolios and credit losses on these loans will not impact firm provisions or capital.
- Loans with missing close dates or that were originated prior to 1980 are removed. This impacts a tiny portion of loans—which becomes smaller every year as these older loans pay off—and is needed due to limited historical macroeconomic data during this period.
- Loans in U.S. territories are removed. These loans account for an extremely small portion of the portfolio (0.01 percent of total balances). Given the small number of loans at issue, the challenges of adjusting the model to score them, including querying and validating historical macroeconomic data for these regions, outweigh the model performance improvements. Furthermore, in most cases, domestic home equity balances generally exclude loans to borrowers in U.S. territories (see FR Y-9C instructions at 391, glossary entry for "Domestic Office").

[316] For example, commercial loans where a single loan is secured by multiple properties in different states are reported with property state missing. Without property state, the model will not run.

Next, the models also account for missing or misreported data on the FR Y-14M report. While firms are responsible for ensuring the completeness and accuracy of data reported in the FR Y-14 information collection, the Board makes efforts to validate firm-reported data and requests resubmissions of data where errors are identified. If data quality remains deficient after resubmission, the Board applies conservative assumptions to a particular portfolio or to specific data, depending on the severity of deficiencies. When origination CLTV or spread at origination is missing, the Board sets these values to the 90th percentile value across all reported loans in the industry in that reporting period. When origination credit score is missing, the Board sets this value to the 10th percentile across all reported loans in the industry in that reporting period.[317] For certain variables, replacement with a conservative value is not an option. The following are cases in which loans are unable to be scored:

- Origination date is missing. Origination date is needed to determine loan age and to merge in origination macroeconomic characteristics, which are used to determine spread at origination and updated CLTV.
- Lien type is neither HELOC nor HEL. Without this information, it is unclear which model should be used to project loss rates.
- Property state is invalid. Property state is needed to determine historical macroeconomic variables such as house price index at origination.
- Origination amount is missing or less than or equal to 0 (for HELs) or origination limit amount is missing or less than or equal to 0 (for HELOCs). Without these fields, important variables such as loan size and utilization (for HELOCs) cannot be determined.
- Unpaid principal balance is missing. This is needed to determine certain variables in the PD model, such as utilization for HELOCs. It is also needed to produce estimated EAD (see Section D.ii.c).
- Next payment due date is missing or invalid. Next payment due date is considered invalid if it is earlier than the origination date. Next payment due date is used to calculate payment status (current, delinquent, etc.).

[317] These 10th and 90th percentile values are calculated separately for HELs and HELOCs. This treatment is consistent with the Board's treatment of erroneous or missing data outlined in Section 2.9 of the Stress Testing Policy Statement.

If a portion or the entirety of a firm's submitted data is too deficient to produce a supervisory loss estimate, the Board, consistent with the Stress Testing Policy Statement, assigns a high loss rate to the share of deficient portfolio balances based on supervisory projections of product-specific home equity losses[318] for other firms.[319] This high loss rate is based on the loss rate path of the 90th percentile firm ordered by loss rates, with the percentiles calculated based on 13-quarter losses. In the case in which no firm is exactly at the 90th percentile, the loss rate path of the firm immediately after the 90th percentile is used. This approach is consistent with the principle of conservatism as detailed in Section 2.9 of the Stress Testing Policy Statement.

Similar to estimation data, macroeconomic data is merged with the FR Y-14M portfolio data. Macroeconomic data both as of the origination quarter of the loan (for instance, to calculate spread at origination) as well as for each projection quarter (for instance, to calculate the percent change in HPI) is merged for use in the model. Historical macroeconomic data is sourced from the historical data used to produce the Stress Test Scenarios; projected macroeconomic data from the supervisory stress test scenario is sourced from the Board's Stress Test Scenarios.[320] Data are merged at a quarterly frequency. For contemporaneous data, this is necessitated by the model's use of quarterly transitions and aligns with the frequency used in projections. While it is possible to use monthly data for origination data instead, the use of quarterly data simplifies the process and allows for the maintenance of a smaller macroeconomic dataset for merging.

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[318] In other words, deficient HELOC balances are assigned a conservative loss rate based on other firms' HELOC loss rates, while deficient HEL balances are assigned a conservative loss rate based on other firms' HEL loss rates.
[319] The high loss rates are also computed separately for "PCD" and "non-PCD" balances. These terms are defined and explained in Section D.ii.d.
[320] *See* Section III.B of the Enhanced Transparency and Public Accountability Proposed Rule for additional information on certain data cleaning processes that are applied to the variables in the historical and contemporaneous data.

For macroeconomic variables that are merged at the national level (in particular, measures of interest rates), the same macroeconomic variable value is assigned to all loans in a given quarter. Unemployment rate is merged at the state level, based on the state in which the property is located. House price index is merged at the county level when possible, based on a mapping of the reported ZIP code of the property to a county. For ZIP codes that cannot be mapped to a county, or for counties for which house price index is not provided,[321] the state-level house price index is used instead. This process allows for the inclusion of historic house price information at the most granular level available to ensure the model is reflective of true housing market conditions. While historic variation in state unemployment rate and state and county house price indexes are preserved, projected values of these variables under the supervisory stress test scenario are assumed to align with the national macroeconomic path. State-level unemployment is assumed to have the same absolute quarter over quarter change in each quarter as the projected national level unemployment rate, while state and county house price indexes are assumed to have the same percentage quarter over quarter change in each quarter as the projected national house price index. Assuming consistent macroeconomic conditions across geographies is consistent with the practice for other models used in the supervisory stress test to ensure that loans are not unduly penalized due to the geography in which they are located. For more detail on the treatment of regional macroeconomic variables in the scenarios, see Section III.B of the Enhanced Transparency and Public Accountability Proposal.

Additionally, a small number of loans are removed from the FR Y-14M data used to project loss rates if variables exceed certain pre-defined thresholds. These loans are removed because they reflect outliers and the model may not be calibrated appropriately to project default

[321] House price index is not reported for all counties. Generally, smaller counties with fewer housing transactions are less likely to have house price indices available.

rates for these loans. Instead, these loans are assigned the loss rate path of the 90th percentile firm, as described earlier in this section. These thresholds are defined below. In all cases, these thresholds impact less than half of one percent of loans reported in the FR Y-14M data, and do not materially impact projected losses:

- Original loan amount (for HELs): Less than $100 or greater than $10,000,000
- Original credit limit (for HELOCs): Less than $100 or greater than $10,000,000
- Property value at origination: Less than $10,000 or greater than $12,000,000

Additionally, the model caps HELOC loan terms at 40 years; loans with reported terms longer than 40 years are treated as outliers and assumed to have 40-year loan terms. While loan term is not directly included in the model, the model uses the loan term to determine whether a HELOC has a balloon payment.[322] Approximately 1 percent of HELOCs in data reported as of December 2024 have reported terms greater than 40 years; however, given the model's limited use of loan term, this condition will only impact projections for loans that (1) have a draw period of greater than 36 years; and (2) will reach within one year of the end of this draw period in the projection period. Given the rarity of loans persisting for more than 30 years in the data, this condition has minimal impact on projections.

Similarly, interest rates (both current and at origination) are top-coded at 50 percent; a loan with a reported interest rate above 50 percent is assumed to have a 50 percent interest rate, as the Board has determined that any such entries likely reflect data errors or extreme outliers, in the Board's experience and expertise. Credit scores are also bounded to be between 300 and 850,

[322] Since the length of time between the end of the draw period and end of the loan term is not directly reported, it is imputed based on the difference between the original loan term, rounded to the nearest year (FR Y-14M, Schedule B.1, Line Item 37) and the allowable draw period, rounded to the nearest year (FR Y-14M, Schedule B.1, Line Item 28).

matching the expected range of the distribution of most of the commercially available credit scores reported on the FR Y-14M.

Payment status (current, delinquent, etc.) is assessed based on certain variables reported on the FR Y-14M to align with the definition used for estimating the model in the Home Equity Data. Loans are treated as defaulted, for the purposes of supervisory modeling, if they are more than 180 days past due—based on the elapsed time between the reported "Next Payment Due Date" and the reporting month. Otherwise, the field "Loan Status (MBA method)" is used, with definitions intended to align with the treatment in the Home Equity Data. Loans marked as "Paid Off" (coded as "0") are treated as paid off; loans marked as "Real Estate Owned" (coded as "R") are treated as defaulted; loans marked as 90 or more days past due (coded as "9") or in foreclosure (coded as "F") are treated as delinquent; and loans that are less than 90 days past due (coded as "C," "3," or "6") are treated as current. Other loans (for instance, with an "Unknown" loan status) are not assigned a payment status or modeled.

The Home Equity PD Model includes a term to indicate previous delinquency so that loans that previously were delinquent can be assessed separately from loans that were not delinquent. Generally, previous delinquency is defined using the historical reported data of a loan. This requires an adjustment in certain cases when a loan (or portfolio of loans) was sold from one reporting institution to another. In the case of such a sale, the Board works with the acquiring institution to maintain the compatibility of loan IDs before and after the sale, such that the complete loan history of acquired loans can be used when possible.

Some small data manipulations are necessary to apply the model parameters to the FR Y-14M data. To align the formatting between the Home Equity Data and the FR Y-14M data, reported FR Y-14M LTVs and CLTVs are multiplied by 100. Origination LTV and CLTV is further cleaned as follows, and data errors are replaced with the conservative 90th percentile value:

- Original LTV and CLTV are bounded at the top end at 125; higher values are reset to 125. Original LTV and CLTV values less than or equal to 0 are assumed to be data errors. Original LTVs and CLTVs above 125 are rare and are likely errors or extreme outliers, occurring in less than 0.1 percent of loans in the Home Equity Data used to estimate the model.
- When the loan is not a first lien loan, the model assumes that there is a data error if original CLTV is less than or the same as original LTV. Since LTV is based only on the loan itself, while CLTV includes more senior liens as well, CLTV should be strictly higher than LTV if the loan is not a first lien.
- Original CLTV is less than original LTV by more than 1 percent for loans that are first liens (for example, for a loan that is marked as a first lien, this condition is triggered if the original LTV is reported as 80 percent and original CLTV is reported as less than 79 percent). For first liens, original LTV and original CLTV are expected to be identical; small differences are allowed as long as they are within this 1 percent tolerance to avoid overly filtering the data.
- Original LTV is less than original CLTV for loans that are first liens. In these situations, CLTV is used instead.

Additionally, utilization is top coded at 250. Note that for all HELOCs, original credit limit rather than current credit limit is used to minimize data errors arising from reporting issues in the current credit limit field.

Finally, the overwhelming majority of credit scores reported in the FR Y-14M follow a scale ranging from 300–850.[323] As long as scores appear to generally follow the same scales, no adjustments are made based on the vendor or version of the score used. Should a situation arise in the future in which a substantial number of loans are reported using a different scale, the Board may consider making adjustments to the scores as they enter the model to ensure consistency.

[323] In the FR Y-14M instructions, firms report the origination credit score as well as the vendor and version of the score.

Loans that are defaulted at the beginning of the projection period are not run through the model; these loans are treated separately. Loans that have not reached terminal status are fed into the Markov chain framework to produce quarterly estimates of default and payoff probabilities.

(4) Alternatives

Alternative Model Structures

The Home Equity PD Model uses a loan-level, multi-period, state transition model approach, which projects the probability in each quarter of a loan transitioning from its existing state to one of several other states. This approach is valuable in the context of the stress test, which requires the projection of home equity loan loss rates over the course of a hypothetical recession.

As discussed in the review of literature in Section D.ii.a.(2), the public domain includes numerous examples of models for simulating credit events. The Board considered a wide range of approaches in determining the appropriate model.

The decision to use a loan-level model is based on the large number of loan and borrower characteristics that impact the default and payoff risk of home equity loans, and the availability of loan-level data reported on the FR Y-14M. There are academic studies (see Hale, Krainer, and McCarthy, 2020) that suggest that modeling using more aggregated portfolio data can produce more accurate projections. In particular, the authors of that paper suggest that using a loan-level model, along with aggregated macroeconomic data, can lead to measurement error. For instance, while the model can account for unemployment rates increasing in a given area, the stress test scenarios do not account for whether an individual borrower experienced job loss; as a result, this must be estimated based on aggregated data—in this case, the state-level unemployment rate. Despite these concerns, a loan-level approach allows for much more granular differentiation compared to a top-down approach that does not consider individual loan characteristics. Loan-level models are widely used in academic and industry contexts,[324] and the large body of literature provides useful context for developing an accurate, robust model of home equity PD. Relying on a loan-level approach is particularly valuable in the context of the supervisory stress test, as an aggregate approach, while capable of producing reasonable industry-level results, may struggle to capture important variation across firms in projecting default rates. Given the availability of granular data, the Board therefore chooses to use a loan-level approach.

The determination to use a multi-period model, as opposed to a single-period model, is necessitated by the design of the stress test. The stress test uses quarterly loss estimates to produce projections of the balance sheets of covered institutions over a nine-quarter horizon. This substantially limits the utility of model structures that produce a single estimate of losses, rather than a path. The chosen multi-period transition model approach provides quarterly projections of default and payoff rates, allowing for projections of not just the total default rate but its shape.

Additionally, consistent with the mortgage literature, the competing risks of default and payoff are considered. While this approach adds complexity to the model, it significantly improves model accuracy. Prepayment rates vary for mortgages depending on the macroeconomic environment and characteristics of the loan; the modeling approach allows for these factors to be internalized in the model. Payoff rates are further used in the supervisory

[324] *See* Section D.ii.a.(2).

stress testing context to determine the amount of balance that runs off a firm's balance sheet in each quarter, which is used to determine the level of new originations.[325]

Given these choices, the Board considered other model structures for projecting a multi-period, semi-annual model, in addition to a state transition model. These alternatives are reviewed in detail in the review of literature in Section D.ii.a.(2). In summary, key alternatives include a simple multinomial logit approach or a hazard model approach. A simple multinomial logit approach is less appealing as this approach does not allow loans to shift into an intermediate delinquent status and is thus less predictive of default risk in a multi-period setting. A hazard approach is valuable for its ability to incorporate unobserved differences between loans. It is also operationally less taxing than a transition model, especially when considering the past states of loans in the model (such as previous delinquency). However, it does not allow for the tracking loans through the different transition states—which update dynamically—which is important in incorporating the shape and persistence of the contemplated macroeconomic shock. Given these factors, and consistent with many industry applications, the Board has selected the state transition model framework rather than alternative approaches.

Alternative Covariates

Based on a literature review and the Board's experience and expertise, the Board considered a large number of variables for inclusion in the model. This section describes alternative specifications of the transition equations and the determinations that led to the alternatives not being chosen. Broadly, variable choices are made to maximize economic support and statistical fit (as defined in Section D.ii.a.(2)).

[325] As previously noted, the supervisory stress test assumes that a firm's balance sheet will remain constant throughout the projection period; new origination balances are set to be equivalent to the sum of loss balance and payoff balance in a given quarter. For more information on the new origination process, *see* Section D.ii.d.

In cases in which the above considerations do not provide a clear best option, and multiple options appear to be equally sound, the Board relies on the stress testing principles to determine the appropriate model, consistent with the Stress Testing Policy Statement. For instance, the Board considers the principle of simplicity to enable a more straightforward interpretation of the drivers of model results and to minimize operational challenges for model implementation. The Board also considers the principle of conservatism to select the model that produces higher loss estimates when multiple approaches are equally sound.

The Board considered simplifying the transition equations, particularly the transitions from current loan status that have a large number of variables, to reduce the number of covariates and make changes to model projections more easily interpretable. However, all variables in the transitions provide sufficient explanatory power to justify their inclusion.

Certain variables are not included in the model, despite evidence that these variables do improve model performance. These cases are outlined below:

- While current credit score is a meaningful predictor of nonpayment, this variable is often missing in the Home Equity Data. Origination credit score is instead used to avoid the data availability constraint. By using origination rather than current credit score, the model does not take into account changes in borrower credit score since origination. However, the Board has determined that using origination credit score, which is more widely available, is reasonable and is a strong predictor in the equations in which it is used.
- Debt-to-income (DTI) ratio is associated with non-payment, as borrowers more burdened by payments are more likely to become delinquent, especially during times of economic stress.[326] However, this variable is not ultimately used due to insufficient data coverage, as it is frequently unavailable in the Home Equity Data.

Certain variables included in the HELOC equations are not included in the HEL equations due to differences in loan characteristics. Namely, variables such as utilization and end-of-draw are not applicable to HELs and thus are not used.

[326] *See* Jagtiani, J. and W.W. Lang, 2011, "Strategic Default on First and Second Lien Mortgages During the Financial Crisis," Journal of Fixed Income, Spring, 7-23.

The Board considered alternative specifications of the six transition equations from delinquent. While many of the same variables that impact transitions from current also conceivably impact transitions from delinquent, the equations are estimated with fewer variables. Furthermore, the transitions from delinquent tend to have worse overall performance (measured by area under the curve, or AUC) compared to the transitions from current. However, a simpler approach was chosen to avoid over-fitting and preserve the robustness and stability of the model, in line with the stress testing principles of simplicity, robustness, and stability. Most notably, transitions from delinquent are observed more rarely in the data, leading to a sparser estimation dataset. With sparser data, the inclusion of too many variables can lead to unreliable estimates. This can be partially accounted for by over-sampling delinquent loans; however, even with a larger sample, model fit did not substantially change. An additional factor is that the transitions from delinquent are less systematic than transitions from current, which makes modeling these transitions challenging regardless of data constraints or the number of variables included.[327]

Macroeconomic characteristics are included in the model to account for increases in home equity PD rates during stress periods. House prices, unemployment rate, and various interest rate indicators are included in the model. The Board uses house prices in the model to account for the level of equity a borrower has in the collateral; as described in the review of literature in Section D.ii.a.(2), the level of equity a borrower has is fundamental to whether a borrower becomes delinquent or defaults. The Board uses unemployment rates to proxy for broad economic stress and households' ability to pay bills, based on academic literature on credit risk, industry best practices, and the Board's experience and expertise. Unemployment rates are

[327] In general, research on the factors that lead delinquencies to progress to default is sparser than that of predicting initial delinquency. Gardner et al (1989) provide valuable research on this issue. Gardner, Mona J., Dixie L. Mills and John Gardner. "Evaluating the Likelihood of Default on Delinquent Loans." Financial Management 18 (1989): 55.

broadly used in this context because they provide a comprehensive measure of the economic health of households and businesses. Higher unemployment rates can be an indication of stress on household budgets. These situations can lead households to default on their loans. The importance of the unemployment rate is observed in academic literature across different retail loan products, including HELOCs (Hale, Krainer, and McCarthy, 2020); but also first lien mortgages (see, for example, Elul, Souleles et al., 2010) and credit cards (see, for example, Agarwal and Liu, 2003; and Belotti and Crook, 2013). The Board considered other indicators of economic strength such as disposable income and real GDP growth, as well; ultimately, unemployment rate was sufficient to account for household economic conditions.

The model takes into account variation in historical house price index and unemployment rate by applying house price indexes at the county level (or state level, if county level is unavailable) and by applying unemployment rate at the state level. For the house price index, the model uses county-level data to account for the local nature of housing markets. For the unemployment rate, the Board considered using county-level variation but determined that state-level variation was a more stable indicator of household labor market conditions. Because labor market conditions tend to be regional, the county- level unemployment rate may not accurately reflect the labor market conditions faced by an individual in that county; at higher levels of geography, such as states, this is less likely.

With respect to interest rates, a wide range of inputs were considered for inclusion in the model. Given the differences between HELOCs and HELs with regard to interest rate sensitivity, these considerations are discussed separately for the two products.

HELs are almost always fixed-rate products, meaning that the interest rate does not change after origination. As a result, changes in market interest rates after origination do not change the payments owed by the borrowers and therefore do not directly impact a borrower's ability to repay the loan, meaning they are not informative for the current-to-delinquent transition equation. On the other hand, interest rates are meaningful in the current-to-payoff transition equation, as they impact a borrower's ability to refinance into cheaper debt. Within the current-to-payoff equation, the interest rate variables included are the change in the 10-year yield from origination through the previous quarter and the change in the 10-year yield over the most recent year. Other interest rate variables (such as the 5-year yield or the 30-year average mortgage rate) were considered, but the 10-year yield appropriately proxies for the behavior of HEL interest rates. The change from origination is calculated through the previous quarter's value rather than the current quarter's value to reflect that consumer behavior tends to lag economic conditions.

For HELOCs, interest rates generally are variable, so changes in market interest rates (generally, the prime rate) can directly impact borrower payments. Generally, economic theory would assume that a higher interest rate would lead to higher payments, and thus higher rates of nonpayment. In fact, the opposite is true in the current-to-delinquent equation, as the key variable—the change in prime rate from origination through the previous quarter—enters the model with a negative sign on its coefficient. This is likely because this term is proxying for the fact that the prime rate tends to decline during periods of economic stress rather than directly proxying for payment shock. Similarly, while higher interest rates are generally associated with lower payoff rates (as the cost of borrowing is more expensive), the HELOC model estimates show that increases in the prime rate are indicative of higher prepayment, likely due to borrowers valuing access to additional liquidity during economic stress. The Board considered other specifications that would separate these effects, such as allowing the impact of changes in the prime rate to vary depending on whether it is positive or negative. Ultimately, the Board determined that while these alternative specifications may improve model performance in certain economic environments, given that the home equity market is small, the changes in projected PD did not appear to affect projected losses by an amount sufficient to impact projected capital levels at the industry level. Alternative specifications also add complexity to the model, which is inconsistent with the stress testing policy of simplicity. Despite this decision, the Board will continue to evaluate the model specification to determine if there are other ways to account for the different ways changes in interest rates impact the risk of HELOCs becoming delinquent and defaulting.

Alternative Data Sources

The Home Equity PD model is built using the Home Equity Data, a loan-level dataset reported from servicers of HELs and HELOCs. The Board could also use the FR Y-14M report itself,[328] which could fit the model parameters and is reported monthly by FR Y-14 reporters with material home equity portfolios.

One advantage of the FR Y-14M data is that reported loans are representative of the population of loans for which the supervisory stress model is used to project losses. Since the Home Equity Data may include loans from certain lenders that are not FR Y-14 reporters, and may not include loans from certain lenders that do report on the FR Y-14, the Home Equity Data loan population may not be reflective of the loan population for which the model is used to project losses. If the loan characteristics vary in ways that are not observed or included in the model, these differences could cause inappropriate loss projections.

Despite this representativeness concern, the Home Equity Data is used due to its longer time series. The FR Y-14M coverage does not begin until June 2012, limiting the visibility these

[328] Specifically, Schedule B.1, which is comprised of home equity loan-level data.

data provide into the behavior of home equity products during the 2008 financial crisis period, the most significant stress event in the housing market in recent history. These periods are crucial for estimating the impacts of falling house prices on performance.

To assuage representativeness concerns, the Board compared the distributions of key fields in overlapping periods between the Home Equity Data and FR Y-14M data and found that, in the Board's qualitative judgment, they were generally similar.[329] The Board has also performed limited testing on an alternative model in which the Home Equity Data and FR Y-14M data are combined and jointly used to fit the model parameters. Limited analysis indicated that this alternative specification would likely lead to changes in losses of less than 5 percent at the industry level; given the small size of the home equity portfolio, these differences are unlikely to impact firm capital requirements. Because of the small changes in projections, and the complexity of combining the datasets, the Board determined that combining the datasets is not appropriate at this time. Despite this finding, the Board may in the future use the combined dataset to improve data representativeness while ensuring coverage of the 2008 financial crisis period. In the meantime, the Board regularly compares key variable statistics between the two datasets to ensure the continued representativeness of the Home Equity Data.

(5) Questions

Question D1: The Board seeks comment on whether the HELOC model specification should be adjusted to improve model sensitivity to changes in market interest rates over time.

Question D2: The Board seeks comment on the decision to treat default as a terminal state in the model, as opposed to an alternative assumption that would allow defaults to cure.

[329] Compared features include origination credit score, payment status, loan vintage, property state, and CLTV at origination. The largest discrepancy is related to account status, as the Home Equity Data often marks loans as paid-off when they in fact defaulted. As noted in Section D.ii.a.(3), this issue is corrected prior to fitting the model parameters.

Question D3: The FR Y-14M instructions allow firms to report a variety of commercially available credit scores. While this provides flexibility to reporting institutions, it raises concerns that if the same credit score value is associated with different risk levels for credit scores taken from certain vendors or certain versions, the model may produce inappropriately high or low PD projections. How should the Board accommodate the inclusion of different credit scores while avoiding inappropriately favoring or penalizing loans reported with certain credit scores?

b. Loss Given Default Model

(1) Description

The Home Equity LGD Model projects the percent of the loan balance that the lender will not be able to recover after the borrower enters default. When a borrower enters default, the lender can sometimes recover a portion of the value of the loan via proceeds from the sale of the collateral or other sources.

The Home Equity Model draws on the First Lien LGD Model to produce projections of loss given default (or "loss severity"). The First Lien LGD Model is described in detail in Section C.ii.b in the First Lien Model Description. In short, the model first projects the elapsed time between when the loan defaults and when it is liquidated (a loan is considered liquidated when the underlying property is sold), then uses this elapsed time (the "timeline") to project the share of the loan balance that cannot be recovered, referred to as the loss severity. This section focuses on the model transformations applied to the First Lien LGD Model to project LGD for home equity products.

First, for home equity products (specifically HELOCs)[330] that are first liens, no adjustment is needed. The First Lien LGD Model is applied directly to the first lien HELOCs as if they were first lien mortgages, directly outputting a loss severity rate for each first lien HELOC.

For other HELOCs and HELs, the First Lien LGD Model is applied to the corresponding first lien mortgage secured by the same property based on available information. The projected loss severity for the first lien is then used to calculate the total recovery associated with the property. The model assumes recoveries will flow to the first lien (or any senior liens) until that lien is entirely paid off before any recovery is realized on the HELOC or HEL. Thus, recovery for the HELOC or HEL is determined by applying the First Lien LGD model to the first lien balance, and if the projected recovery amount exceeds the first lien balance, the excess is realized as recovery on the HELOC or HEL.[331]

Mathematically, LGD for second liens is defined based on Equation D3:

Equation D3 – Home Equity LGD Calculation

$$LGD = 1 - \frac{Net\ Recovery}{Unpaid\ principal\ balance\ at\ default}$$

where net recovery is defined as in Equation D4:

Equation D4 – Net Recovery Calculation

$$Net\ Recovery = First\ Lien\ Balance * (1 - LGD_{FL}) - First\ Lien\ Balance$$

[330] Only HELOCs, not HELs, can be first liens, since the home equity model is only applied to junior lien HELs.
[331] For the purposes of the LGD model, all outstanding loan balance on the property senior to a given loan is treated as the first lien balance. Specifically, first lien balance is calculated as the CLTV on the HEL or HELOC at origination multiplied by the property value of the HEL or HELOC at origination minus the original balance of the HEL or HELOC. The first balance is assumed to not change from origination, as information on the balance path of the first lien after origination is unobserved.

where the first lien balance is calculated as described below in this section, and LGD_{FL} (which can in theory be negative, zero, or positive) is the output from the First Lien LGD Model applied to the corresponding first lien, as described below.

Note that in all cases, LGD is required to be no less than zero and no greater than one. Negative values of LGD are assumed to be zero (no loss), while values of LGD greater than one are assumed to be one (complete charge-off).

The first lien loan amount is assumed to be the first lien balance at the time of origination. In cases in which some of the first lien balance has been paid down between the origination of the first lien loan and the origination of the HEL or HELOC, the model will underestimate loan balance. However, as original balance—like many characteristics of the first lien—are not observed in the FR Y-14M data,[332] the balance at the time of home equity origination serves as the best available proxy for the original balance.[333]

To calculate the recovery on the corresponding first lien to determine the LGD for the HELOC or HEL, the other components of the First Lien LGD model are determined as follows:

- Collateral type (used to assign loans into one of three LGD equations): In the First Lien LGD model, collateral type is determined based on credit score at origination, LTV at origination, and income documentation type. Given the lack of information about the first lien loan, a simplified mapping is used to set collateral type for home equity loans. Loans with origination (at the time of home equity origination) credit scores below 620 are treated as subprime; loans with credit scores above 720 or loans with credit scores above 680 with full income documentation are treated as prime; and all other loans are treated as Alt-A.[334] These decisions are informed by the Board's expertise and experience. The Board investigated using alternative definitions of collateral type to align more closely with the definitions used directly in the First Lien LGD Model. While the alternative definitions would increase consistency across models, the impact on modeled loss rates is virtually zero for all firms. Given the lack of sensitivity to changes

[332] Given that the first lien may have a different lender, requiring the collection and reporting of historical and contemporaneous data on the first lien on FR Y-14M, Schedule B.1 (Home Equity) would be unduly burdensome, given that the data as of home equity origination serves as a reasonable proxy in many cases.
[333] This proxy is reasonable given the slow rate at which first lien balances amortize over their terms. For instance, Board analysis of historical data reported on FR Y-14M, Schedule A.1 (First Lien) notes that on average, first lien balances in a given snapshot represent between 80 percent and 90 percent of the first lien origination amount.
[334] Alt-A is a classification of loans that are less risky than subprime loans but riskier than prime loans.

in the collateral type definition, the Board assessed that the current definition is appropriate.

- Origination loan-to-value (LTV) ratio: The first lien origination LTV is assumed to be equal to the first lien loan balance at the time of the home equity origination divided by the property value at the time of the home equity origination. This is the best assessment of LTV available in the home equity data; however, it may not align with the true origination LTV if the home value or loan balance changed between the origination of the first lien loan and the origination of the HEL or HELOC.
- Mark-to-market LTV ratio: This is the origination LTV multiplied by the ratio of origination house price index divided by projected house price index at the projected liquidation date. House price index is incorporated into the model at the county level (or state level if county is unavailable), identical to the PD model. As data on first lien balance is not available after origination, this calculation does not incorporate any amortization on the first lien loan between origination of the HEL or HELOC and the projected liquidation date.
- Timeline: As in the First Lien LGD Model, the timeline in this equation is defined as the elapsed time between when the loan reaches 90 days past due and when it is liquidated, which is assumed to be 25 months[335] for all loans.
- Loan size: As stated above, the first lien loan amount is assumed to be the first lien balance at the time of origination. Specifically, first lien balance is calculated as the CLTV on the HEL or HELOC at origination multiplied by the property value of the HEL or HELOC at origination minus the original balance of the HEL or HELOC.
- Property type (2-4 Family, Condo, Planned Unit Development): This is reported on the FR Y-14M report for the HEL or HELOC; the first lien value is assumed to be the same, as the loans are secured by the same property. Single family properties are the "base case;" they are accounted for based on when loans are not any of the property types listed out above.
- Occupancy type (Investor Owned, Second Home): This is reported on the FR Y-14M report for the HEL or HELOC; the first lien value is assumed to be the same, as the loans are secured by the same property. Loans for primary residences are the "base case;" they are accounted for based on when loans are not any of the occupancy types listed above.
- Loan purpose (Refinance, Cash-out Refinance): This is reported on the FR Y-14M report for the HEL or HELOC; the first lien value is assumed to be the same, as information on the first lien purpose is not reported.
- Origination credit score: The credit score is assumed to be the credit score at the time of HEL or HELOC origination, as the credit score at the time of first lien origination is unknown.
- State foreclosure type: Historically, loss severity has been higher in states with judicial foreclosure compared to states with widely used non-judicial foreclosure options. However, to avoid penalizing loans based on the state of the property, a single value is applied to loans regardless of property state. This value is calibrated based on the share of loan balance reported in the FR Y-14M in a given period that are in states with judicial foreclosure processes. Effectively, the model treats all loans as if they are

[335] The model assumes that 22 months elapse between default and liquidation. The additional three months are added to reflect the time elapsed between when a loan reaches 90 days past due and when it defaults.

probabilistically located in a judicial or non-judicial state based on the share of loans in each category across the industry. By construction, the first lien loan has the same property state as the HEL or HELOC. States are defined as judicial or non-judicial based on Cordell and Lambie-Hanson (2016).[336]

- Vintage: The loan vintage (year of origination) is assumed to be the same for the first lien as it is for the HEL or the HELOC, as the true first lien origination date is not reported.
- Year-over-year percent change in house price index: This term is identical for all loans in a given geography liquidating on the same date.
- Post-2010 flag: This is reported as "1" for all loans, reflecting that all projected liquidations will occur following the start of the projection window.

In certain cases, the above assumptions may not be correct, especially in cases in which the first lien was originated at a different time than the HEL or HELOC, but they serve as the best available proxies given limited insight into details about the first liens.

If the LGD on the first lien is positive, the recovery on the HEL or HELOC is assumed to be 0 (in other words, the LGD is 100 percent). If the LGD on the first lien balance is negative, the recovery on the HEL or HELOC is assumed to be the remaining recovery amount after the first lien balance has been paid off. For instance, if the LGD on the first lien is calculated as -10 percent, then the recovery amount on the HEL or HELOC is assumed to be 10 percent of the first lien balance. This recovery amount is then divided by the HEL or HELOC balance to produce an estimate of LGD.

In all cases, LGD is never allowed to be less than 0 or greater than 1 (100 percent). In the case that estimated LGD is less than 0, LGD is assumed to be 0; in the case that estimated LGD is greater than 1, LGD is assumed to be 1.

(2) Support for Model Decisions

The Home Equity Model applies the First Lien LGD Model to project LGD for home equity products, which include both first lien and junior lien products. For junior lien HELs and

[336] Cordell, Larry, and Lauren Lambie-Hanson. 2016. "A Cost-Benefit Analysis of Judicial Foreclosure Delay and a Preliminary Look at New Mortgage Servicing Rules," Journal of Economics and Business, 84: 30–49.

HELOCs, a small number of adjustments are made to the model. This section outlines the support for applying the First Lien LGD Model to the home equity portfolio. Support for the design and specification of the First Lien LGD Model can be found in the discussion of the First Lien Model contained in Section C.ii.b in the First Lien Model Description.

The First Lien LGD model is well suited to first lien loans with losses projected by the Home Equity Model (in particular, first lien HELOCs). While HELOCs have many characteristics that are different from closed-end, first lien mortgages, at the time of default they are both loans secured by residential real estate. Since recovery is driven by the collateral, the First Lien LGD model is appropriate for these loans.

For junior liens, the model is determined by the legal mechanics of the mortgage market. Contractually, first liens must be paid off in full before junior liens receive any recovery. By first calculating the recovery value, then netting out the value of the first lien loan, the model appropriately accounts for lien seniority.

As detailed previously in this sub-section, certain assumptions about the first lien loan must be made to use the LGD model for home equity loans, given the absence of dynamic data on the first lien reported in the FR Y-14M. In general, loan and borrower characteristics are assumed to be static from the time of home equity origination. These assumptions reasonably approximate the characteristics of the first lien loan while substantially reducing the burden to reporters of collecting and regularly updating information on senior liens.

(3) Adjustments and Data Cleaning Steps

Adjustments and data cleaning needed to produce the Home Equity LGD Model parameters are outlined in the discussion of the First Lien Loss Model contained in Section C.ii.b in the First Lien Model Description. This section briefly discusses certain data cleaning steps used to apply the model to the home equity loan data reported on FR Y-14Q, Schedule B.1.

The process for treating missing data is identical to that of the Home Equity PD Model. Loans that are not scored in the PD model are also not assigned LGD. These loans are given a conservative loss rate as outlined in D.ii.a.(3). Similarly, loans with missing credit scores at origination or CLTV at origination are assigned a conservative value based on the industry distribution. This process is also outlined in Section D.ii.a.(3).

The process for incorporating macroeconomic data (in particular, home price index) is identical to that of the Home Equity PD Model. In particular, macroeconomic data is merged with the FR Y-14M portfolio data. Macroeconomic data is included both as of the origination date of the loan as well as the projected quarter of liquidation.[337] Historical macroeconomic data is included as described in this model description;[338] projected macroeconomic data from the supervisory stress test scenario is sourced from the Stress Test Scenarios. These data are merged at a quarterly frequency to align with the frequency of model projections. For origination data, it is possible to use monthly data instead; however, the quarterly data simplifies the process and allows for the maintenance of a smaller macroeconomic dataset.

House price index is merged at the county level when possible, based on a mapping of the reported ZIP code of the property to a county. For ZIP codes that cannot be mapped to a county, or for counties for which house price index is not provided,[339] the state-level house price index is used instead. This process allows for the inclusion of historic house price information at the most granular level available to ensure the model is reflective of true housing market conditions.

337 Liquidation quarter is projected based on the Timeline model.
338 The source of macroeconomic variables aligns with that of equivalent variables used in the PD Model.
339 House price index is not reported for all counties. Generally, smaller counties with fewer housing transactions are less likely to have house price index available.

While historic variation in state and county house price indexes are preserved, projected values of house price index under the supervisory stress test scenario are assumed to align with the national macroeconomic path. State and county house price indexes are assumed to have the same percentage quarter-over-quarter change as the projected national house price index. Assuming consistent macroeconomic conditions across geographies is consistent with other models used in the supervisory stress test (see Section III.B of the Enhanced Transparency and Public Accountability Proposal) to ensure that loans are not unduly penalized due to the geography in which they are located.

(4) Alternatives

As an alternative, the Board could develop a separate model for projecting LGD for home equity products instead of determining the recovery available for junior liens by using the First Lien LGD Model. Developing a separate model would have the benefit of accounting for characteristics particular to junior liens, such as certain workout programs, and avoid the need to make assumptions about the characteristics of the first lien loan. Despite these potential benefits, the chosen approach is preferable for the following reasons:

- While historic loss data on first lien mortgages is available through public datasets or vendor data, historic loss data on junior liens is much less robust, especially when considering the 2008 financial crisis era. Without historic loss information, fitting the parameters is challenging.
- The largest determinant of recoveries for loans secured by real estate is the value of the collateral. While the recovery available to a lender may vary based on the existence of senior liens, the property value itself is generally unrelated to the number of loans by which it is secured. Therefore, the Board's approach is economically justified.
- Losses on junior liens are generally very high during periods of economic stress, approaching or reaching 100 percent LGD for most loans. This finding is consistent with historical firm-reported data on FR Y-14M, Schedule B.1 (Home Equity), Line Item 104 (Loss Given Default – LGD). As defaulted loans often do not produce enough of a recovery to pay off the first lien during a housing crisis, it is unlikely that junior liens will receive much, if any, recovery under these circumstances. Given this, the difficulty of developing and implementing a separate Home Equity LGD Model is not justified by the

limited variation in outcomes it would introduce. The Board's approach thus aligns with the stress testing principles of simplicity and consistency.

The Board has also considered alternative specifications given the use of the First Lien LGD Model to model LGD for HELs and HELOCs.[340] One alternative is to replace the approximated values of the first lien variables used in the model with other values. These other values could either be included in the FR Y-14M report or approximated in a different manner. For instance, the balance of the first lien at liquidation could be approximated based on expected amortization of the first lien loan between the home equity origination date and the projected liquidation date. These alternative specifications of the input values could improve model accuracy in certain cases. However, the model described in this sub-section is used instead to ensure model simplicity, consistent with the Stress Testing Policy Statement. Adding fields to the FR Y-14M would substantially increase reporting burden, as the reporting institution would be required to regularly update fields relating to a loan separate from the loan being reported. In many cases, the first lien may not have the same lender or loan servicer as the HEL or HELOC, limiting the reporting institution's visibility into information about the first lien. Given this reporting burden, the Board does not propose adding these additional fields to the schedule. Further, making different assumptions about the first lien projected values at liquidation would require adding additional complexity to the model and would only produce small changes in the projected loss rates. The increased complexity and reduced interpretability are not justified by the limited potential improvement in model performance.

[340] Note that alternative specifications of the First Lien LGD model itself are discussed as part of the discussion of the First Lien Model in Section C.ii.b of the First Lien Model Description. In this section, the First Lien LGD model itself is treated as given.

An additional consideration is the treatment of "add-ons" such as accrued interest or carrying costs. Accrued interest refers to interest charges that are accrued but unpaid, which can be capitalized into loan balance at the time of default. The Board reviewed these accrued interest charges and determined that these reductions may already be accounted for in the net interest income component of the pre-provision net revenue model. To avoid potentially double counting these losses both via reductions in net revenue and credit losses, these charges are excluded from the LGD calculation. Carrying costs refer to the implicit costs to the firm that arise from the delay between when the loan defaults and when the proceeds of the sale of the property are provided to the firm. This is potentially costly to the firm as the present value of the recovery may be lower if it is not received until long after the loan has defaulted. Carrying costs are also accounted for through the pre-provision net revenue model; however, when the liquidation process extends outside of the nine-quarter stress test horizon, additional carrying costs may not be included. Because foreclosure and liquidation can take significant time for mortgages, these costs could theoretically be significant for certain products, such as first lien mortgages. However, the Board reviewed historical FR Y-14M data to assess the time that generally elapses between when the loan becomes 180 or more days past due and when it is terminated. This elapsed time is generally much lower for HELs and HELOCs compared to first lien mortgages, as these loans are often charged off in full rather than liquidated through foreclosure. Given this finding, carrying costs do not significantly impact total LGD; when considering that only carrying costs outside of the nine-quarter horizon are excluded from the pre-provision net revenue estimates, the impact is even smaller. Given this small impact, and the additional complexity required to incorporate carrying costs into LGD, these costs are excluded when calculating loss severity.

(5) Questions

Question D4: The Board seeks comment on whether to develop a model specifically for projecting Home Equity LGD, as opposed to using the First Lien LGD Model, with adjustments to allow the model to project LGD for junior liens.

Question D5: The Board seeks comment on any possible changes to the First Lien LGD Model that would allow it to better project LGD for home equity exposures, considering that these changes may also change projections of First Lien LGD.

Question D6: The Board seeks comment on whether it is appropriate to incorporate measures of accrued interest and carrying costs into total losses when projecting Home Equity LGD.

Question D7: To project Home Equity LGD, the Board makes several assumptions about the characteristics of the first lien to which a junior lien home equity exposure is linked. The Board seeks comment on whether to adjust any of these assumptions.

c. Exposure at Default Model

(1) Description

The Home Equity Exposure at Default (EAD) Model is used to determine the total outstanding loan balance at the time of default. The Board assumes EAD for HELs to be the unpaid principal balance of the loan at the start of the projection horizon. HELOCs that have been permanently closed or have reached the end-of-draw period are essentially closed-end loans. For these HELOCs, the Board assumes EAD to equal the unpaid principal balance at the start of the projection horizon. The EAD for these HELOCs and for all HELs can be described mathematically as in Equation D5:

Equation D5 – EAD for HELs and HELOCs that are Closed or Have Reached End of Draw

$$EAD = UPB_0$$

where UPB_0 is the unpaid principal balance at the start of the projection horizon.

For all other HELOCs, the Board sets EAD to the higher of the unpaid principal balance at the start of the projection horizon and the original credit limit, as shown mathematically in Equation D6:

Equation D6 – EAD for Open HELOCs

$$EAD = \max(UPB_0, OCL)$$

where UPB_0 is the unpaid principal balance at the start of the projection horizon and OCL is the original credit limit of the loan.

(2) Support for Model Decisions

The EAD Model considers three different cases: (1) a HEL; (2) a HELOC that is marked as closed or has reached end-of-draw; and (3) an open HELOC that has not reached end-of-draw. Each of these cases is discussed separately.

HELs

Closed-end, junior lien home equity loans are assumed to have EAD equal to the loan balance at the start of the projection period. This simple assumption produces conservative estimates of EAD, as it does not account for any amortization of the loan during the projection horizon. In particular, the historical Home Equity Data and FR Y-14M data demonstrates that

HELs are generally fixed rate, amortizing loans, meaning that loan balance tends to decline over time as borrowers make scheduled payments.

Despite the conservatism of this approach, it is reasonable. The impact of amortization on HEL balances over short time horizons is small, as HELs tend to have long terms during which balances decline slowly if paid according to their contractual terms. Additionally, EAD is set to project balances of defaulting loans; as loans proceed to default, and borrowers miss scheduled payments, balance decline will stall. Meanwhile, accounting for amortization would require the development of a more complex model, reducing interpretability of results and increasing operational burden and model processing time. Given the limited impact and the lack of certainty of the true EAD, the Board assumes that EAD is equal to unpaid principal balance at the start of the projection horizon, consistent with the Stress Testing principles of conservatism and simplicity.

HELOCs (Marked as Closed or After End-of-Draw)

Generally, HELOCs are open-ended, meaning that the borrower can continue to make draws following the origination of a loan. However, after the end of the contractual draw period,[341] the ability to make new draws closes, and the outstanding balance must be repaid. Similarly, in some circumstances firms will close HELOCs;[342] once a HELOC is closed, no further draws can be made. In these circumstances, HELOCs behave similarly to closed-end loans. Given that the contractual obligations in these cases are similar to closed-end loans, the

[341] In cases where the draw period is projected to end during the projection horizon, the Board treats the HELOC as open until the projected end-of-draw date, and then closed after.
[342] Servicers may permanently close lines if borrowers exhibit repayment difficulties or if the lender is no longer willing to extend a line of credit as large as that provided at loan origination, which can occur if area house prices have fallen, threatening the collateral value of the property.

Board treats closed HELOCs and HELOCs that have reached end-of-draw identically to HELs for the purposes of projecting EAD.

HELOCs (Other)

Loans that neither are marked as closed nor have reached end-of-draw are assumed to still be open, meaning borrowers are able to make additional draws on their lines of credit. As a result, there is significant uncertainty in the path of balances through the projection horizon. Borrowers could repay part of their principal, maintain their current balance, or make additional draws prior to default.

Economic intuition, as well as analysis of the Home Equity Data and FR Y-14M data, provides evidence to support the conservative assumption that borrowers will draw down the entire remaining credit line prior to default. Intuitively, borrowers benefit from information asymmetries that incentivize making large draws. In particular, borrowers may have advanced notice of their individual situation before lenders do. In this context, such circumstances can include a reduction in income (job loss), new expenses (for instance, medical bills), or a change in collateral value (borrowers may anticipate changes in home values before the lenders can react). In these situations, in which borrowers know they are likely to default but that information has not reached the lender, the borrower is incentivized to draw down available credit before the lender becomes aware and the line is closed. Analysis of Home Equity Data and FR Y-14M data provides support for this view. In particular, the Board assessed the behavior of open HELOCs in the years leading up to an eventual default to assess whether borrowers made additional draws shortly before defaulting. In general, the analysis shows that changes in balance immediately prior to default follow one of two patterns: either no additional draws are made or all (or virtually all) of the remaining balance is drawn. During the trough of the housing market in the 2008 financial crisis period, nearly half of defaulting borrowers in the Home Equity Data drew down their entire available line of credit.[343] As the housing market recovered, the share of borrowers drawing down their credit prior to default declined; however, it is unclear whether this decline is due to improved risk management by lenders or due to differences in borrower behavior during a crisis versus during less stressful periods. Given the uncertainty and the incentives for borrowers with information advantages, the Board, in line with the principle of conservatism and to enable the model to evaluate the impact of severe economic stress, assumes that borrowers will draw down their remaining balances for the purposes of modeling in the supervisory stress test.

Unpaid principal balance may be greater than the original credit limit in situations in which the credit limit has been raised or the borrower has overdrawn the line. In these situations, consistent with the principle of conservatism, the unpaid principal balance is used as the EAD.

When the HELOC EAD model is applied to historical data, the EAD projections are consistent with historical outcomes in the run-up to the 2008 financial crisis period, providing further support for current modeling decisions.

One consideration in the calculation of EAD is that the Board calculates EAD based on the original credit limit of the HELOC rather than the current credit limit. In situations in which the credit limit changed between origination and the start of the projection horizon, this could lead to over- or under-predicted exposure at default. Despite this potential for inaccurate EAD projections, using the original credit limit has certain advantages over using the current credit limit. First, in situations in which the credit limit drops temporarily, such as when a HELOC is frozen, the current credit limit may not be reflective of the available balance during the

[343] Most of the remaining borrowers made no additional draws; however, some borrowers did draw down part, but not all, of their available credit.

projection horizon—when the line may become unfrozen. Next, origination credit limit is stable over time, while the current credit limit can vary; additional assumptions must be made to apply the current credit limit over the projection horizon. Additionally, credit limits change infrequently for HELOCs (more than three-quarters of HELOCs in the data used to fit the model parameters had identical current and origination limits; of the remainder, most differences were assessed by the Board to be minor), so the use of the current credit limit leads to similar EADs compared to the use of the original credit limit. Finally, a mitigating factor to the impact of the use of the original credit limit is that original credit limit is used in both PD and EAD. If the current credit limit is lower than the original credit limit, EAD could potentially be over-projected; however, this is mitigated by the fact that the utilization variable in the PD model will have a lower value, reducing projected PD. Based on all these factors and the principles of simplicity and consistency and comparability, original, rather than current, credit limit is used to project EAD.

(3) Adjustments and Data Cleaning Steps

No additional adjustments or data cleaning steps are applied.

(4) Alternatives

HELs

As stated in Section D.ii.c.(2), an alternative approach is to incorporate projected amortization into the EAD model. Incorporating amortization would generally reduce EAD as balances on term loans decline over time.

Despite the potential advantages of accounting for amortization, the Board determined that the benefits of doing so do not outweigh the costs. The impact of amortization on HEL balances over short time horizons is small, as HELs tend to have long terms during which balances decline slowly. Additionally, EAD is set to project balances of defaulting loans; as discussed in Section D.ii.c.(2), as loans proceed to default, balance decline stalls. Meanwhile, accounting for amortization would require the development of a more complex model, reducing the interpretability of results and increasing operational burden and model processing time. Given the limited expected impact and the lack of certainty about the true EAD, the Board assumes that EAD is equal to the unpaid principal balance at the start of the projection horizon, consistent with the Stress Testing principles of conservatism and simplicity.

HELOCs (Marked as Closed or After End-of-Draw)

As noted previously, HELOCs marked as closed or having reached end-of-draw function as closed-end loans. Given the behavior and characteristics of these HELOCs, potential alternatives are the same as for HELs, as described above.

Another alternative approach is to treat HELOCs that are marked as closed or have reached end-of-draw similar to other HELOCs while making assumptions about future draws. However, assuming future draws would not be consistent with the contractual terms of these HELOCs, as doing so would require the line to be reopened. Given these contractual terms, treating HELOCs that are closed or have reached end-of-draw as closed-end loans, similar to HELs, is appropriate.

HELOCs (Other)

HELOCs that are not closed and have not reached end-of-draw (referred to as "open HELOCs" in this sub-section) are assigned EAD equal to the larger of the unpaid principal balance at the start of the projection horizon and the original credit limit. Given the nature of these loans as open-ended, revolving lines of credit, the potential balance changes ahead of default are complex. Theoretically, open HELOC balance could increase, decrease, or stay the same over time.

The Board considered three alternative approaches to setting EAD for open HELOCs. First, the Board considered treating open HELOCs similarly to HELs, in effect assuming no additional draws on the HELOC during the projection period. Second, the Board considered assuming a fixed percentage of the remaining available credit would be drawn prior to default. Finally, the Board considered developing a formal regression model through which EAD would be determined based on certain loan, borrower, and macroeconomic characteristics. These alternatives are discussed separately below.

Assuming no additional draws on a HELOC has the benefit of simplicity. This alternative would remove the need to consider credit limit for EAD and would simplify the operational process by allowing a single process to account for all HELs and HELOCs. It would also account for firms' monitoring practices, which often allow for the freezing or closing of lines that are at risk of default. However, the assumption of no additional draws is inconsistent with historical data reported both in the Home Equity Data and the FR Y-14M, which show that borrowers often do make draws prior to defaulting, as discussed in Section D.ii.c.(2). These draws are incentivized by information asymmetry, as discussed in that section. While firms have reduced these information asymmetries since the 2008 financial crisis period by improving portfolio monitoring, there is risk that during a housing crisis, a sudden deterioration in market conditions will not provide firms an opportunity to apply risk mitigation efforts prior to the borrowers making additional draws. Not allowing for any new draws on open HELOCs would have led to the model underpredicting EAD during the run-up to the 2008 financial crisis period, the most notable prolonged period of housing market stress in recent history. Given these drawbacks, the Board opted against assuming no additional draws.

Assuming a fixed percentage of the remaining available credit will be drawn prior to default has certain advantages. Under this assumption, EAD would be expected to be at least equal to the principal balance at the start of the projection period, but less than the original credit limit. For instance, if this percentage is set to 50 percent, the principal balance of a given loan at the start of the projection period is $10,000, and the origination credit limit of that loan is $20,000, then the EAD would be set to $15,000 ($5,000 of the remaining $10,000 in available credit would be projected to be drawn). An advantage of this approach is that it allows the supervisory stress test model to account for the potential for some additional drawn balance without over-estimating such draws. The percentage applied to this calculation could be calibrated based on historical default data. However, this approach may not be appropriate given that, as described in Section D.ii.c.(2), borrowers historically tend to either draw down their entire remaining balance or not make any draws; intermediate draw amounts are unusual. An average could be calibrated based on the share of borrowers that draw their entire balance; however, while this would produce reasonable industry-level numbers, it could lead to under-prediction of EAD for certain subsets of borrowers that are more likely to draw prior to default. Given the uncertainty around draws during periods of housing market stress and across borrowers, the Board applies the principle of conservatism in determining a preference for the chosen modeling approach.

A final alternative the Board considered involves the implementation of a formal regression model to calibrate EAD based on loan, borrower, and macroeconomic characteristics. The Board tested the application of such a model. In this alternative model, the share of the undrawn balance that is projected to be drawn prior to default is dependent on certain variables, such as utilization and the seasoning of the loan. The Board performed historical back-testing analysis on the resulting model, which showed model projections accurately tracked historical draw over time. However, the regression model adds substantial complexity to the home equity modeling framework. Given that the home equity market is small, the Board did not consider changes in EAD to affect projected losses by an amount sufficient to impact projected capital levels at the industry level. Because of this small aggregate impact, the Board determined that the cost of the increased complexity is greater than the associated benefit of more calibrated EAD projections. As a result, in line with the stress testing principle of simplicity, the Board determined that assuming a full drawdown of the undrawn balance is appropriate for the supervisory stress test.

Given this modeling choice, the Board also considered which of the two HELOC credit limit fields in the FR Y-14M to use in the model. The EAD for open HELOCs is the greater of the unpaid principal balance and the original credit limit. An alternative assumption is to base the EAD on the current credit limit rather than the original credit limit. Using the current credit limit would account for changes in the credit limit of the HELOC between origination and the start of the projection period. However, as outlined in Section D.ii.c.(2), using the original credit limit slightly simplifies the approach, avoids the need for additional assumptions about changes to the credit limit over the projection horizon, and has a minimal impact on projected losses. Given these considerations, the original credit limit, rather than the current credit limit, is used to set EAD for open HELOCs.

(5) Questions

Question D8: The Board is seeking comment on whether to model the amount of balance for HELs, and HELOCs that are closed or have reached end of draw, that is amortized during the projection period, as opposed to setting exposure at default for these loans to the principal balance at the start of the projection period.

Question D9: The Board is seeking comment on alternatives to the assumption that HELOCs that are not closed and have not reached end of draw will draw the entirety of the undrawn balance prior to default, including projecting that a partial share will be drawn.

d. Model Integration and Projection

(1) Description

The model projects loss rates and payoff rates by applying the PD, LGD, and EAD models to loans from the FR Y-14M Home Equity schedule. In each quarter, the PD model produces a probability of default and a probability of payoff for each loan. The projected losses for a loan in a given quarter are the product of PD, LGD, and EAD in that quarter. The projected payoff rate for a loan is directly produced by the PD model.

Next, the loan-level default and payoff projections are aggregated. Projected paid-off balance, defaulted balance, and total balance are summed for each firm within each product type (HELOC or HEL). These totals are further split into purchased credit deteriorated ("PCD") balances and balances that are not purchased credit deteriorated ("non-PCD") based on the "Purchased Credit Deteriorated Status" variable[344] reported in the FR Y-14M. For a given firm and product type, loss and payoff balances are divided by total balances separately for PCD and non-PCD balances to produce loss and payoff rates for each group.

[344] Y-14M, Schedule B.1, Line Item 60. Accounting practices vary for loans purchased credit deteriorated from other loans.

Loans that are in defaulted status at the start of the projection horizon are treated separately. These loans are not run through the PD, LGD, or EAD models; instead, it is assumed that these loans will receive a 100 percent loss rate, divided evenly across the first six projection quarters, to smooth the impact of the defaulted loans on the stress test results.

In addition to projecting losses on the portfolio of loans reported on FR Y-14M, Schedule A (First Lien), referred to as the "existing portfolio," the model is used to project losses on a hypothetical portfolio of new originations. New origination loss rates and payoff rates are projected similarly to existing portfolio loss and payoff rates. The portfolio characteristics are assumed to remain constant for new originations, consistent with the stress test assumption of a constant balance sheet, with the exception that new originations are assumed to be current (not delinquent), the loan age field is reset to zero, and the "vintage" fields (used to assess the enhanced risk of loans originated in certain years) are reset to zero as well. For HELOCs, the draw period from origination is assumed to be the same as the original loan; end-of-draw is assumed to be reached only after the length of the original draw period has elapsed. Additionally, all HELOCs are assumed to be open at origination, and payments are assumed to be interest-only for HELOCs reset to pre-end-of-draw.

The result of this process is a dataset that produces, for each reporting firm, and for each product type, three projected loss rates and three projected payoff rates corresponding to existing non-PCD loans, existing PCD loans, and new origination[345] loans.

Additionally, the share of balances to be assigned a conservative loss rate based on missing data, as described in Section D.ii.a.(3), is produced for each firm and each product type separately for PCD and non-PCD balances.

[345] New origination losses are assumed to all be non-PCD.

The projections produced in this section are applied in the Retail Loss Aggregation process, detailed in Section D.ii.e.

(2) Support for Model Decisions

The model integration process is generally mechanical, aggregating results from across the model components. This section supports certain parts of the process where assumptions are made.

Existing Defaults Assigned 100 Percent Losses, Spread Evenly Over 6 Quarters

For loans that are 180 or more days past due at the beginning of the projection horizon (or trigger other default conditions), the PD model is not applied. This is because the loans have already reached terminal status, so further transitions from default are not possible. For operational simplicity, the LGD model is not applied either; instead, the loan is assigned LGD of 100 percent. This is the most common LGD assigned to loans in the Home Equity Model, as home equity loans tend to be junior liens; running these loans through the LGD model would minimally impact projected losses under stress.

Spreading losses on loans starting in default across six quarters prevents the loans from all being charged off at once at the start of the projection, which would create unreasonably high provision estimates in the first projection quarter. Since the model for these loans is deterministic (they will default with 100 percent probability), an assumption of the exact timing of loss would ignore the inherent uncertainty in the loan resolution process. Six quarters are chosen to align with the principle of conservatism, which suggests that defaulted loans should be charged off expeditiously, while avoiding the creation of an artificial bunching effect from assuming all existing defaults will be charged off simultaneously.

PCD and non-PCD Loans are Projected Separately

The accounting procedures for PCD and non-PCD loans vary, as PCD loans are credit deteriorated at the time of purchase. Prior to firm adoption of the Current Expected Credit Loss ("CECL") accounting framework, the book value of PCD loans was reduced by the amount of the expected credit loss. To account for this, the supervisory stress test model separates out these balances and applies an adjustment in Retail Loss Aggregation (see Section D.ii.e for more information) to credit against PCD losses. With the adoption of CECL by firms, this is no longer necessary; however, the continued separation of these balances is not problematic. For this reason, PCD and non-PCD balances are separated, despite the additional complexity it adds to the modeling framework.

New Originations are Generally Assumed to Have the Same Characteristics as the Existing Portfolio

This assumption that new originations have the same characteristics as those in the existing portfolio is consistent with the constant balance sheet assumption applied across the supervisory stress test models, which states that firm balance sheets are expected to remain constant across the stress test horizon. Exceptions are made for certain dynamic variables based on reasonability:

- By definition, newly originated loans are unseasoned and should have zero months on book.
- Similarly, new loans are assumed to have been originated during the projection period; they cannot be older vintages, including the 2006 or 2007 vintages that are directly incorporated into the PD model.
- Loans are assumed to be in current status at origination. It is unreasonable to assume that a loan could already be 90 or more days past due upon origination.
- New HELOCs are assumed to have open lines, as open-endedness is a key feature of these loans.

(3) Adjustments and Data Cleaning Steps

No additional adjustments or data cleaning steps are applied.

(4) Alternatives

Given that the model integration process is a straightforward application of the PD, LGD, and EAD components, no specific alternative implementations were considered.

e. Retail Loss Aggregation

(1) Description

Retail Loss Aggregation refers to the process by which the Board uses the outputs described in the previous sections to produce final projections of loss dollars. In particular, the process begins with the reported portfolio balances and the projected loss rates and projected payoff rates described in Section D.ii.d for each quarter for each firm participating in the supervisory stress test reporting data on FR Y-14M, Schedule B.1 (Home Equity), for the existing portfolio as well as the projected new origination portfolio. From there, the Board applies a series of calculations and adjustments, described in detail below. The output of the Retail Loss Aggregation process is a final projection of loss dollars for each firm in each sub-portfolio (HEL and HELOC) in each quarter.

Calculation of Existing Portfolio Losses and Payoffs

In Retail Loss Aggregation, the projected loss rates are assigned to the balances of HELs and HELOCs produced by the balance sheet line-item projections calculator based on data reported in FR Y-14Q, Schedule M.1 (Balances).[346] In particular, HEL balances are taken from line item 1.a.2.a, column A (CALBP336), while HELOC balances are taken from line item 1.a.2.b, column A (CALBP340). Loss rates are computed separately for non-PCD and PCD

[346] *See* Section A in the Aggregation Models Documentation (Balances Model).

balances. Total PCD and non-PCD balances are derived from FR Y-14Q, Schedule M.3.[347] Subject to the adjustments described below in this section, projected loss rates on the existing portfolio (separately for PCD and non-PCD) are multiplied by these balances in each of the 13 projection quarters to produce existing portfolio loss dollars. Similarly, payoff balances for the existing portfolio are produced by multiplying the modeled payoff rates by these balances.

Calculation of New Origination Losses and Payoffs

After calculating projected loss and payoff balances for the existing portfolio, new origination balances in each quarter are calculated as the sum of the dollar amount of payoffs and losses in that quarter from the existing portfolio (as well as any additional loss or payoff amounts from new originations in previous quarters). This process implies that over the projection horizon, firms will originate loans with balances equal to the total balances that rolled off in a previous quarter, consistent with the supervisory stress test assumption of a constant balance sheet. Furthermore, the path of loss rates and payoff rates for each vintage of new originations is assumed to be identical, consistent with the stress testing principle of simplicity. For example, the loss rate and payoff rate path for loans originated in the second projection quarter is the same for those originated in the fifth projection quarter. The sum of existing non-PCD, existing PCD, and new origination loss dollars is the total loss dollar amount for the portfolio, subject to the adjustments below.

[347] Formally, the unpaid principal balance of PCD loans in a portfolio is taken directly from FR Y-14Q, Schedule M.3, Part I (for HELs, line item 1.a.2.a, column D, denoted by CALBR762, for HELOCS, line item 1.a.2.b, column D, denoted by CALBR766), and the unpaid principal balance of non-PCD loans is calculated as the book value reported on FR Y-14Q, Schedule M.3, Part I (for HELs, line item 1.a.2.a, column A, denoted by CALBR759; for HELOCS, line item 1.a.2.b, column A, denoted by CALBR763) plus the total.

Adjustment for Non-Delinquent Non-Accrual Loans

Total loss dollars are adjusted for non-delinquent non-accrual ("NDNA") loans. NDNA loans are junior lien loans that are current and secured by the same property as a delinquent senior lien. Since the home equity model does not consider the performance of an accompanying first lien loan, it does not account for the possibility that the senior lien may be delinquent. However, a delinquent first lien may indicate that the borrower is facing financial stress and potential repossession of the collateral; in these situations, the junior lien is likely to eventually default. To account for this enhanced likelihood of default, an adjustment is made to account for projected losses on NDNA loans. This adjustment is consistent with interagency guidance issued in 2012.[348] In particular, the Board assumes a share of current loans are junior to delinquent first lien loans and assumes these loans will default with 100 percent probability. The share of NDNA loans is assumed to be equivalent for PCD and non-PCD loans, in line with the stress testing principles of simplicity and consistency. In the supervisory severely adverse scenario, these loans are projected to have an LGD of 100 percent, reflecting that recoveries for junior liens are unlikely during periods of economic stress; as a result, the model assumes 100 percent loss rate on NDNA balances (no additional draws are projected on these balances). To calculate the share of balance to be adjusted, the Board uses data reported on FR Y-14M, Schedule C (Address Matching) to link loans secured by the same property in 2013.[349] Based on this linked data, the

[348] "Interagency Supervisory Guidance on Allowance for Loan and Lease Losses Estimation Practices for Loans and Lines of Credit Secured by Junior Liens on 1–4 Family Residential Properties." Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation, National Credit Union Administration, and Office of the Comptroller of the Currency. (31 January 2012), http://www.occ.gov/news-issuances/news-releases/2012/nr-ia-2012-15a.pdf.

[349] Data from 2013 were used as this was the first year that reliable address-matched data were available on the FR Y-14M report. Using data from 2013, as opposed to more recent periods, conservatively assumes NDNA rates will return to their immediate post-crisis levels during a hypothetical stress event. The Federal Reserve regularly analyzes the NDNA data from more recent periods to assess the impact of updating the estimated share of NDNA balances and has determined that any changes would be unlikely to meaningfully impact a firm's calculated stress capital buffer.

Board determined that 0.94 percent of HELOC balances and 1.41 percent of HEL balances meet the NDNA criteria. These NDNA losses are added to other losses projected on HELs and HELOCs.

Calculation of Losses on Commercial Loans

As noted in Section D.ii.a.(3), certain loans reported on FR Y-14M, Schedule B.1 (Home Equity) are commercial loans and are therefore not modeled using the Home Equity Model. These loans generally represent a small portion of the home equity portfolio, comprising less than 1 percent of total balances reported on the schedule. Losses are assigned separately in Retail Loss Aggregation. To assign losses on commercial loans, the share of balances reported on FR Y-14M, Schedule B.1 (Home Equity) that are commercial is first calculated for each firm and product type (HEL or HELOC), both among PCD and non-PCD loans (referred to as "Commercial Weights"). Next, for each product type, separately for PCD and non-PCD balances, the share of balances of severely delinquent loans, defined as loans that are 90 or more days delinquent or in foreclosure or repossession, is calculated for both commercial and non-commercial loans. It should be noted that severely delinquent balance shares are calculated at the industry level rather than by firm; as certain firms have very small commercial portfolios, the calculated shares can become unreasonably extreme at the firm level. With these severely delinquent industry shares calculated, the Board calculates the ratio of the severely delinquent shares among commercial and non-commercial loans (referred to as "Commercial Factors") for each product type separately for PCD and non-PCD loans.

The Commercial Weights and Commercial Factors are next used to assign losses to commercial balances. For each firm and product type, separately for PCD and non-PCD balances, the share of balances that are commercial (defined by the Commercial Weight) is assigned losses equal to the modeled loss rate for that firm and product type (separately for PCD and non-PCD balances) multiplied by the PCD or non-PCD Commercial Factor for that product type. For instance, if a firm's modeled HELOC non-PCD loss rate (inclusive of the NDNA adjustment above) is 5 percent, the firm's Commercial Weight is 10 percent, and the industry Commercial Factor is 1.1x, the firm's HELOC non-PCD loss rate inclusive of the commercial adjustment is calculated as 5 percent multiplied by 90 percent (the Commercial Weight subtracted from one) plus 5 percent multiplied by 10 percent (the Commercial Weight) multiplied by 1.1 (the Commercial Factor), or 5.05 percent. This adjusted loss rate is multiplied by portfolio balances using the procedure described in the second paragraph of this section to produce loss dollar estimates. This calculation is described mathematically in Equation D7:

Equation D7 – Commercial Loan Losses

$$
\begin{aligned}
Loss\ Rate_{s,i,t} = {} & (1 - Commercial\ Weight_{s,i}) * Modeled\ Loss\ Rate_{s,i,t} \\
& + Commercial\ Weight_{s,i} * Modeled\ Loss\ Rate_{s,i,t} \\
& * Commercial\ Factor_{s}
\end{aligned}
$$

where:

- *s* refers to the segment (four total, corresponding to segments for PCD and non-PCD, each for HELs and HELOCs);
- *i* refers to the firm, *t* refers to the projection quarter;
- $Loss\ Rate_{s,i,t}$ refers to the firm's loss rate in the segment;
- $Commercial\ Weight_{s,i}$ refers to Commercial Weight, as defined in the previous paragraph;
- $Modeled\ Loss\ Rate_{s,i,t}$ refers to the firm's loss rate in the segment in a given projection quarter, as calculated in Section D.ii.d; and
- $Commercial\ Factor_{s}$ refers to the Commercial Factor in the segment, calculated at an industry level.

Application of Credits Against Already-Realized Losses

Next, both PCD and non-PCD losses (inclusive of the NDNA and commercial adjustments described above) are netted against certain credits for loans of each product type (HEL or HELOC) that have already been charged off. Failing to consider these credits would lead to double counting of these losses. For PCD loans, credits are assumed to be equal to the difference between the unpaid principal balance and the book value[350] reported on FR Y-14Q, Schedule M.3,[351] and credits are applied on a "first-loss first-credited" basis. In other words, the amount of PCD losses is reduced by the level of credits until no further credits remain; at that point, no further reductions are made. For non-PCD loans, credits are assumed to be equal to the "Cumulative Interim Loan Losses" reported on Part II of FR Y-14Q, Schedule M.3, which total the balances the firm has previously charged off against loans that are still active on its balance sheet.[352] The Board applies these non-PCD credits evenly over the first six projection quarters to be consistent with the treatment of defaulted loans in the supervisory stress test. The net losses are calculated as the losses calculated in the previous paragraph for a given firm and product type (HEL or HELOC) minus the credits described in this paragraph.

Calculation of Projected FDIC Shared Loss Agreement Payments

Finally, losses are reduced to account for coverage provided by shared loss agreements (SLAs) with the Federal Deposit Insurance Corporation (FDIC). As part of the resolution of a

[350] Unpaid principal value is the total principal amount outstanding as of the end of the reporting period for a given product (HEL or HELOC, separated by PCD vs. non-PCD) and does not include any accounting-based write-downs. The book value is consistent with the values reported on FR Y-14Q, Schedule M.1 and does include certain accounting adjustments.

[351] Historically, the difference between unpaid principal balance and book value on this schedule for the predecessor of PCD loans ("PCI" loans) reflected the credit discount marked at the time of purchase. However, under the CECL accounting standard, this is no longer the case, as the discount is now instead included in the allowance for credit losses. The Federal Reserve analyzed the process of assigning credits for PCD loans and concluded that the materiality was small; therefore, the procedure.

[352] Following the adoption of CECL, this field no longer is limited to Cumulative Interim Loan Losses on non-PCD balances; however, in practice, the vast majority of balances are non-PCD.

failing institution, the FDIC may enter into an agreement with the purchaser to absorb a portion of certain losses on specific assets.[353] To avoid unduly penalizing firms for loan losses covered by SLAs, the Board reduces home equity losses to account for this coverage. In particular, the Board has proposed collecting the balances of HELs and HELOCs covered by SLAs on the FR Y-14Q.[354] The share of losses covered by SLAs is assigned based on the terms of the individual SLA reported by the FDIC. Finally, loss rates on the portion of the balance covered by the SLA are assumed to be the same as the loss rate on the entire existing portfolio.[355] In total, losses on a portfolio are reduced by the covered percent of the projected losses on covered balances, as calculated above.

Treatment of Immaterial and Missing Portfolio Data

The process described above in this section produces loss dollars for firms reporting data on FR Y-14M, Schedule B (Home Equity); however, certain firms that report HEL or HELOC balances on FR Y-14Q, Schedule M.1 (Balances) do not report on FR Y-14M, Schedule B (Home Equity).[356] For firms not reporting on the FR Y-14M, Schedule B that are not required to do so, balances are assigned, consistent with Section 2.10 of the Stress Testing Policy Statement, the loss rate path and payoff rate path of the firm with the 50th percentile loss rate among firms reporting FR Y-14M, Schedule B (Home Equity). These loss rates and payoff rates are calculated separately for PCD and non-PCD exposures; because new originations are assumed to

[353] *See* "Shared Loss," Federal Deposit Insurance Corporation, https://www.fdic.gov/franchise-sales/shared-loss.
[354] *See* proposed instructions for FR Y-14Q, Schedule M.4. Until these instructions are finalized, the Board may collect this information via a special data collection.
[355] SLA balances are assumed to be cover equivalent shares of PCD and non-PCD balances (and equivalent shares of CRE balances within these categories). No adjustment is made for SLA coverage of new origination loans, as new originations are by construction not purchased from the FDIC.
[356] Firms are required to report FR Y-14M, Schedule B, Home Equity schedule if portfolio balances are material, as defined in the FR Y-14M instructions. Firms with portfolio balances that are below the materiality threshold have the option of submitting or not submitting the schedule. The Board uses reported data to produce loss estimates for firms whenever possible, even if the reporting institution is below the materiality threshold.

be non-PCD exposures, the new origination loss rate and payoff rates are based on the 50th percentile of existing non-PCD loss rates.[357] With these loss rates and payoff rates assigned, the Retail Loss Aggregation process is applied, as described above.[358] For firms not reporting FR Y-14M, Schedule B (Home Equity) and that are required to do so, the process is the same as for firms with immaterial portfolios, except that, consistent with Section 2.9 of the Stress Testing Policy Statement, the Board assigns these exposures the loss rate and prepay rate paths of the firm with the 90th percentile loss rate among firms reporting FR Y-14M, Schedule B (Home Equity). In either case, if no firm is exactly at the 50th or 90th percentile, the firm with the loss rate immediately above this level is used.

Additionally, as described in Section D.ii.d, among firms that do report FR Y-14M, Schedule B (Home Equity), a portion of the balance may be assigned a conservative loss rate if it cannot be run through the model. This balance is assigned the 90th percentile loss rate path (separated by product type and separately for PCD and non-PCD exposures), as described in the previous paragraph.

Total losses described throughout this sub-section are used in the downstream Provisions Model[359] to produce estimates of provisions.

(2) Support for Model Decisions

The Retail Loss Aggregation process produces loss estimates using a simple, consistent process across all retail portfolios. This process ensures adherence to principles of the

[357] In this context, "loss rate" refers to total loss dollars divided by initial portfolio balances, and "payoff rate" refers to the to the total dollar value of payoffs divided by initial portfolio balances. Percentiles are calculated by summing the loss rates over the 13 projection quarters.
[358] Since the commercial weights cannot be calculated for firms not reporting FR Y-14M, Schedule A (First Lien), the Board assumes that immaterial balances are not commercial exposures. This is reasonable, considering the small share of the overall portfolio that consists of commercial exposures. The information required to apply the other adjustments described in this section is available on other schedules that are reported by all firms.
[359] *See* Section B in the Aggregation Models Documentation (Provisions Model).

supervisory stress test, including simplicity, consistency, robustness, and the assumption of a constant balance sheet throughout the forecast period. The assignment of existing portfolio losses described in Section D.ii.e.(1) is a straightforward calculation based on the reported data. Support for the other adjustments and calculations is outlined below.

Assignment of New Origination Losses

New origination losses are assigned based on the expected balances of new originations and the calculated new origination loss rate from the Home Equity Model. The expected balances of new originations and the calculated new origination loss rate are both assigned to be consistent with the assumption of a constant balance sheet through the supervisory stress test horizon. In particular, expected new origination balances in a quarter are set to be equal to the projected run-off from the prior quarter, where the run-off is equal to the sum of projected losses[360] and payoffs in that quarter. The calculated new origination loss rate path relies on the supervisory stress test scenario and assumes that the new origination portfolio is identical to the existing portfolio, except for certain dynamic variables such as loan age and delinquency status, which are reset consistent with the characteristics of a newly originated loan. For more details, see Section D.ii.d.

One simplifying assumption in this process is that each new origination vintage is assumed to follow the same loss rate path, regardless of when in the scenario it is projected to be originated. As a result, new origination loss rates for all vintages are identical and calculated using the start of the scenario path. There is no variation in new origination loss rates based on

[360] Because LGD can be less than 100 percent, using projected losses instead of projected defaulted balance may underestimate the run-off level. However, the vast majority of run-off consists of payoff balance rather than defaulted balance, so the impact of not accounting for recovered balance is small. Using projected balances reduces the complexity of the process by avoiding the need to pass an additional parameter (default rate) downstream from the Home Equity Model through the Retail Loss Aggregation process.

when in the projection period the loans are projected to be originated. This may lead to over- or under-prediction of losses of certain vintages that experience a macroeconomic environment not well reflected by the start of the scenario. However, assigning a single loss rate path substantially reduces the operational complexity of the model; meanwhile, losses on projected new originations only account for just over 10 percent of total projected losses in recent stress test exercises. Therefore, the single loss rate path is used. Given that new origination losses constitute a minority of total losses, and that loss rate paths are similar at different starting points, the Board has determined that the impact of using more loss rate paths would be limited.

Treatment of NDNA Loans

As noted previously, the treatment of NDNA loans is consistent with interagency guidance that requires institutions with junior liens to account for the delinquency status of senior liens that are secured by the same collateral. If no adjustment is made, these junior liens may be assigned inappropriately low loss rates. Calem and Sarama (2017) provide a framework for determining the factors that would lead to borrowers becoming delinquent on their first lien loan while continuing to stay current on their junior lien loan. Borrowers with stable equity positions have an incentive to temporarily mismatch , while borrowers with negative equity and severe financial distress tend to default. The assumption that NDNA loans will default is consistent with these findings due to the severe and prolonged housing market stress contemplated by the supervisory stress test scenarios, and is consistent with the supervisory stress test principle of conservatism. The assumption that NDNA loans will face 100 percent LGD under the severely adverse scenario is reasonable given that LGD projections for junior liens under stress are generally 100 percent.

The share of the portfolio made up of NDNA loans is calculated based on historical data reported on the FR Y-14M report. While the senior lien and junior lien securing a property may be owned by different institutions, the FR Y-14M enables matching loans by property address. This matching allows for the approximation of historical levels of current junior liens on the same property as a delinquent senior lien. Because this is necessarily an approximation and relies on both liens being reported on the FR Y-14M, it is calculated at the industry level over a historical period rather than by firm for each supervisory stress test exercise. This may lead to imprecise results when the share of delinquent first liens is higher or lower than the historical average; however, the imprecision is justified by the simplicity of the process, which reduces the computing resources needed by the Board to produce the model results.

Treatment of Commercial Loans

As described in Section D.ii.a.(3), commercial loans exhibit different historical behavior from non-commercial loans, and are also frequently missing key fields necessary for modeling, such as the state where the property is located.[361] As it is therefore unreasonable to apply the expected loss model to these loans, the Board uses a different process to produce loss estimates for commercial loans.

Commercial loans account for a small minority (less than 1 percent) of total balances reported on the FR Y-14M report. Because of the small number of loans at issue, the Board prioritizes simplicity, as the small number of loans both make it challenging to estimate a model and reduces the benefit of precise model projections. Given the small materiality, scaling losses based on the ratio of severely delinquent balances between commercial and non-commercial

[361] These missing fields, including property state, are driven by the reporting instructions, rather than the failure of reporting institutions to report required fields. For instance, property state is left blank in the case in which a single loan is secured by multiple properties in multiple states.

loans provides a simple solution that accounts for potential differences in risk levels between commercial and non-commercial loans.

One consideration is that by applying the Commercial Factors at the industry level rather than the firm level, the model does not account for variation in commercial loan performance across firms. For instance, if one firm has a less risky commercial loan portfolio than others, this is not accounted for in the model. Despite this limitation, the Commercial Factors are calculated at the industry level because certain firms have very small numbers of commercial loans; a single commercial loan entering delinquency could significantly impact the Commercial Factors if they were assigned at the firm level. To avoid this volatility, the Board uses the industry-level value. If commercial loans were to make up a larger share of portfolio balances, a more complex treatment could be justified to ensure predictions are reasonable; given the small balances at issue, the simple approach provides reasonable loss projections for commercial loans.

Finally, Commercial Weights and Commercial Factors are calculated separately for PCD and non-PCD balances. This reflects that PCD and non-PCD balances may have fundamentally different behavior, as PCD exposures experience known credit deterioration. By separating the calculation, the model ensures that commercial loan losses are set based on portfolio trends rather than differences in the shares of commercial and non-commercial loans that are PCD.

Application of Accounting Credits

As noted earlier in this section, accounting credits are assigned separately for PCD and non-PCD loans. This process is justified by the separate accounting treatment of PCD loans compared to other loans. Prior to the adoption of the CECL accounting standards by firms, the predecessor of PCD loans (“PCI” loans) saw their book value reduced by the amount of expected credit losses at the time of purchase.

As firms have adopted CECL, the distinction has become less meaningful for the application of accounting credits; however, the separation is maintained in the Home Equity Model due to limited materiality and resource constraints.

For non-PCD loans, credits are based on the Cumulative Interim Loan Losses reported on Part II of FR Y-14Q, Schedule M.3. While, given adoption of CECL by firms, Cumulative Interim Loan Losses are not separated for non-PCD loans, the model assumes that all Cumulative Interim Loan Losses are applied to non-PCD loans because non-PCD loans account for the vast majority of balances and because in previous periods when PCD and non-PCD Cumulative Interim Loan Losses were separated, most of the total Cumulative Interim Loan Losses were non-PCD. Cumulative Interim Loan Losses refer to write-downs on loans that remain active on a bank's portfolio, potentially due to the loan being in the repossession or charge-off process. Since the firm has already accounted for these losses, they should not further reduce the firm's capital levels. The model applies non-PCD credits evenly over the first six quarters of the projection horizon. This is intended to be analogous to the treatment of loans in defaulted status at the beginning of the projection period. Given that Cumulative Interim Loan Losses accrue from loans that are already in default, it is reasonable to apply these credits to net against losses projected on defaulted loans. Assigning all the credits in the first projection quarter would be incongruous with the Board's assumption that losses on defaulted loans are spread over many quarters.

For PCD loans, credits are based on the difference between the reported unpaid principal balance and book value reported on FR Y-14Q, Schedule M.3. Prior to firm adoption of CECL, this difference was reflective of the credit discount at the time of purchase; since the firm has already accounted for certain credit losses on PCD loans, it is inappropriate to further penalize the firm for such losses. Given that it is unknown how portfolio-level credit discounts are allocated to various PCD loans, these credits are applied on a first-loss first-credited basis, until all credits have been applied.[362] However, with the adoption of CECL by firms, the credit discount is no longer removed from the book value; as such, the difference between unpaid principal balance and book value no longer reflects the credit discount. Nevertheless, as the assumption that this difference is due to a credit discount has a negligible impact on loss projections, the treatment is maintained.

Treatment of FDIC Shared Loss Agreements

Loans subject to shared loss agreements with the FDIC are partially insured by the government. Balances subject to these agreements can vary substantially over time based on the rate at which failed banks are dispositioned by the FDIC and the terms of such dispositions. Because of this insurance, the Board does not assign losses to the portion of covered balances insured by the FDIC. The terms of the agreement are made public by the FDIC; these terms are used to set the specific loss sharing rate for each portfolio for each firm.

The Board uses the share of the portfolio balances subject to a shared loss agreement (SLA), as reported by a firm, to estimate the amount of losses covered by the agreement. This process implicitly assumes that the characteristics of the portion of the portfolio covered by SLAs are identical to that of the rest of the portfolio. If the portion of the portfolio covered by SLAs is notably riskier or less risky than the rest of the portfolio, this may lead to an inappropriate projection of the share of balances covered by the FDIC. However, addressing the potential for differences in portfolio characteristics would require firms to identify individual loans covered by SLAs, which would increase the reporting burden on firms and increase the

[362] The amount of accounting credits applied to PCD balances in a given quarter is not allowed to be greater than the total of projected losses in that quarter. This implies that net PCD losses for a given quarter are lower bounded by 0.

complexity of the Board's modeling process. To limit the operational burden for both reporters and the Board, this portfolio-level adjustment is used.

Process for Missing and Immaterial Portfolios

The process for missing and immaterial portfolios, as described in Section D.ii.e.(1), is consistent with other models throughout the supervisory stress test to produce reasonable projections while mitigating the burden to reporting institutions, and is aligned with the Stress Testing Policy Statement, as described earlier in this sub-section.

(3) Adjustments and Data Cleaning Steps

Generally, no data adjustments are needed for this step. However, if a firm's submitted data are too deficient to produce a supervisory loss estimate, the Board assigns a high (90th percentile) loss rate to the portfolio balances based on supervisory projections of product-specific home equity (HEL or HELOC) losses for other firms, as described previously. In the case that the Board determines the submitted data to be deficient, the Board can assign this 90th percentile loss rate to the portfolio balances.

(4) Alternatives

A range of alternatives are available both for determining the level of new originations and the treatment of missing data and immaterial portfolios. The Board chose the Retail Loss Aggregation framework to produce reasonable, consistent projections that are consistent with the Stress Testing Policy Statement.

Alternatives to the specific adjustments are described below.

Assignment of New Origination Losses

The Home Equity Model assumes that all new origination vintages follow the same loss rate path. However, as each new origination vintage is necessarily originated in a different macroeconomic environment over the course of the scenarios, this assumption limits the ability of the model to incorporate the different risks impacting different vintages of new originations.

An alternative modeling assumption would be to create different loss rate paths for different vintages by running the model with different macroeconomic scenario paths depending on when in the scenario the loans were originated. While this would provide more precise projections of new origination losses, it would substantially increase the operational complexity of the model. Losses on new originations are a small share of total projected losses, and many of the factors determining losses are loan and borrower characteristics, which would not change, as opposed to the macroeconomic environment, which would. Given the limited impact and increased complexity of producing more than one new origination loss vector, the Board selected the single loss path for new originations to align with the stress testing principle of simplicity.

Treatment of NDNA Loans

The Board considered alternatives to the treatment of NDNA loans, including with respect to calculating the share of the balance projected to be NDNA and the treatment of these balances.

The Board projects the share of balance to be NDNA based on analysis of the FR Y-14M data. Frequently, different firms hold the senior and junior lien on houses with multiple liens. If both liens are owned or serviced by FR Y-14M reporters, they can be identified using address matching on FR Y-14M, Schedule C. However, if the senior lien is not owned or serviced by a FR Y-14M reporter, it cannot be used to assess the payment status of the senior lien.

Given these data limitations, and the additional reporting burden it would require for firms to produce updated information on the senior lien on the property for which they hold the junior lien, the Board relies on the available data to produce the adjustment. However, the limited data availability makes it challenging to update the share of NDNA loans dynamically or to differentiate these shares at the firm level. Instead, the NDNA shares are calibrated for HELs and HELOCs separately at the industry level based on historical data.

The Board also considered alternative treatments for NDNA balances. In benign times, borrowers sometimes cure their delinquent loans and never default on the junior lien. Given this finding, default rates lower than 100 percent could be considered. Per Calem and Sarama (2017), borrowers with one current loan and one delinquent loan on a property are more likely to cure the delinquent loan than equivalent borrowers without a current loan. However, the authors note that negative equity and severe financial distress are associated with borrowers defaulting on both loans. Based on this finding and supporting empirical analysis performed by the Board on data reported on the FR Y-14M, the 100 percent default assumption is appropriate.

Treatment of Commercial Loans

Commercial loans make up a small share of loans reported on the FR Y-14M; a simple adjustment projects losses on these balances.

One alternative approach is to run commercial loans through a separate model based on the factors that are associated with credit losses specific to commercial loans. For instance, the supervisory stress test Commercial Real Estate (CRE) model[363] could be applied to one-to-four family properties with a commercial purpose. The drawbacks to this approach are operational, as relying on the CRE model would significantly burden FR Y-14 reporters. As the FR Y-14 instructions are currently written, loans secured by one-to-four family properties are reported together, regardless of the purpose of the loan as commercial or non-commercial. These instructions are consistent with the FR Y-9C instructions. Requiring reporters to separate and

[363] *See* Section B.

reallocate balances based on loan purpose would require adjustments to firms' internal process, which in the Board's view is not a justifiable burden to place on firms given the small share of loans at issue. Similarly, without adjustments to the reporting procedures, applying the CRE model to these loans would require the Board to implement an operationally complex adjustment process. Additionally, the CRE model is not designed to model revolving credit facilities such as HELOCs that lack key features such as utilization, providing an additional barrier to leveraging the existing CRE model to project losses on HELOCs.

Another alternative approach that is less complex than producing a complete model for commercial home equity loans involves assigning the Commercial Factor at the firm level, rather than the industry level. Assigning the Commercial Factor at the firm level would allow the model to account for firm-specific variation in commercial loan performance. Despite this advantage, the use of firm-specific Commercial Factors would introduce substantial volatility. As some firms have a small number of commercial loans, a change in just a handful of loans' payment status (in some cases, fewer than 100) could drastically change the Commercial Factor to the point where it could notably impact projected losses despite the small size of the portfolio. Given the small materiality of the portfolio, the Board prioritizes stable, reasonable estimates of commercial losses; therefore, the industry-level Commercial Factor is used. The Board may revisit this assumption if balances or projected losses on commercial loans become more impactful in the future.

Application of Accounting Credits

With firm adoption of the CECL accounting standard, accounting treatments for PCD loans differ from their predecessors. Consequently, an alternative approach to assigning credits would involve combining PCD and non-PCD balances in the Retail Loss Aggregation process.

Combining the balances would be consistent with the instructions for Cumulative Interim Loan Losses, which do not require differentiation between PCD and non-PCD losses. This combination would also eliminate the use of the difference between unpaid principal balance and book value for assigning credits on PCD losses. The Board uses the current approach for operational consistency, considering the limited impact of PCD credits on the supervisory stress test results. However, if PCD balances and credits increase in the future, the Board may update the procedure to combine PCD and non-PCD balances.

Treatment of FDIC Shared Loss Agreements

As noted in Section D.ii.e.(2), applying the FDIC SLA adjustment at the loan level, rather than the portfolio level, would allow for a more granular assessment of losses on covered balances. A loan-level adjustment would enable consideration of whether the portion of the portfolio subject to the SLA is more or less risky than other loans in the portfolio, and would allow for the ability to identify loans that are projected to have additional draws prior to default.[364] Despite these advantages, the Board determined that a simpler approach relying on portfolio-level balances would reduce reporting burden and align with the stress testing principle of simplicity while still appropriately considering the insurance provided by shared loss agreements.

An additional alternative to the treatment of loans covered by FDIC SLAs is to treat payments from the FDIC to cover losses as non-interest income, a component of pre-provision net revenue, rather than to net the FDIC coverage against credit losses. This distinction likely has no impact on projected firm capital levels as increases in credit loss expenses on the covered assets would be offset by the income recognized from the increased asset value of the FDIC

[364] The model implicitly assumes that the share of additional draws during the projection horizon from loans subject to the SLA is proportional to the share of portfolio balances subject to the SLA.

SLA. Given that the impact of both approaches is likely identical, and that accounting for the SLA within the credit loss and allowance calculation reduces the Board's operational burden, the supervisory stress test models account for the SLA using the methodology described in this section.

Process for Missing and Immaterial Portfolios

The process for missing and immaterial portfolios is designed to be consistent with the Stress Testing Policy Statement and other models used in the supervisory stress test. While the Board could use alternative values, it determined that a consistent approach ensured fair treatment of firms across different business lines.

(5) Questions

Question D10: The Home Equity model separates losses into PCD and non-PCD exposures. With the adoption of CECL by firms changing the reporting practices for Book Value and Cumulative Interim Loan Losses, should the Board continue to separate these exposures for the purposes of determining accounting credits?

Question D11: Should the Board consider a different process for assigning losses to loans with a commercial purpose instead of using the commercial weights and industry commercial factor described in this section?

Question D12: Should the Board consider a different process for calculating the share of projected first lien losses covered by shared loss agreements with the FDIC?

Question D13: Should the Board consider using a different period of data to calibrate the share of non-defaulted HELs and HELOCs that correspond to defaulted first liens (referred to as "NDNA loans")? Furthermore, should the Board make alternative assumptions about the expected losses on NDNA loans instead of assuming these loans have 100 percent PD and LGD?

iii. Key Assumptions for the Home Equity Model

a. Representativeness of Estimation Data

A key assumption of the Home Equity model is that model parameters are estimated using data from appropriate periods. The data used to produce these parameters (the "estimation sample") does not include data during and after 2020 due to unique challenges associated with the behavior of the home equity portfolio—given the economic environment during the COVID-19 pandemic. During this period, home prices stayed elevated while the unemployment rate initially increased at a historic pace and then declined sharply from its peak. Meanwhile, due to forbearance programs offered by lenders, many borrowers missed payments on their loans, which may not have reflected an inability to pay. This combination of increased delinquency (including borrowers who might have stayed current absent forbearance), high home prices, and temporarily high unemployment presents challenges for the model. These relationships likely reflect the unique circumstances of the COVID shock and will likely not be reflective of future behavior.

Academic research corroborates the view that the economic distortions in 2020 and the years following are significant, and that the observed relationships between the economic environment and borrower behavior during this period are unique. For example, Stock and Watson (2025) find that the COVID shock was notable but had "largely disappeared by late 2022."[365] This finding raises concerns that if data covering 2020–2022 are used to estimate the model coefficients, these coefficients may be impacted by the distortions that caused these unusual observed relationships.

[365] Stock, J. and M. Watson (2025). "Recovering from COVID," NBER working paper 33857.

While the concerns with including this period of data are significant, ending the estimation in 2019 could potentially result in model parameters that do not reflect the current portfolio, as recent periods are not included in the model estimation sample. This could lead to model projections that do not accurately reflect the true level of risk.

To assess this dynamic, the Board has tested incorporating data from more recent periods into the PD model while applying treatments to data during the COVID-19 pandemic period to prevent the model from being unduly impacted by the conditions that arose in 2020. The Board's analysis indicates that the projected loss rates under the model that includes more recent data are broadly similar to (within approximately 10 percent in all cases, and substantially smaller than 10 percent under the most reasonable alternative specifications) the projected loss rates under the Board's preferred model. Based on this analysis, the Board determined that the model's projections are not substantially impacted by the exclusion of recent periods of data. Furthermore, while loss rates remain similar to those produced by the current model, they can vary based on the choice of treatment (or lack thereof) to account for the pandemic period. Given the complexity and ambiguity of accounting for the pandemic period, and the limited materiality of the home equity portfolio, the Board determined that incorporating pandemic data is not appropriate. However, the Board will continue to monitor portfolio characteristics and performance over time to determine if it becomes appropriate to incorporate more recent data into the model.

iv. Alternatives to the Home Equity Model

The Home Equity Loss Model uses an expected loss framework to project loan losses and provisions on domestic home equity exposures. Alternative modeling choices for the individual model components are discussed earlier in Section D.ii; this section describes alternatives to the expected loss framework.

One simple alternative to the expected loss framework is a scalar approach. Under a scalar approach, a single loss rate path is assigned to each firm reporting HELOC balances, and a separate loss rate path is assigned to each firm reporting HEL balances. The scalar can be calibrated based on historical data to align with expectations during a stress period. The scalar approach maximizes consistency by treating loans identically across firms and has the additional advantage of a simple implementation. Furthermore, a scalar approach would substantially reduce the amount of data needed to produce home equity losses, reducing the reporting burden for firms. A scalar approach would also enable explainability; the complexity of the home equity model can in certain cases limit the ability for the public to assess factors that cause loss rates to be higher at certain firms than others. Under a scalar approach, loss rates are not differentiated by firm, removing this challenge. Finally, since home equity exposures among firms subject to the supervisory stress test tend to be small as a share of overall assets—with total balances for home equity comprising only 1.5 percent of total risk weighted assets (RWA) among covered firms—reducing the complexity of the Home Equity Model would not have a substantial impact on firm capital. However, despite these advantages, the expected loss framework is preferable to a scalar approach. The failure of a scalar approach to differentiate loss rates based on observable risk characteristics, such as differences in product type and credit score, severely limits the model's accuracy. For instance, a scalar approach would have difficulty accounting for the shift in portfolios from riskier loans to less risky loans in the aftermath of the 2008 financial crisis as lenders tightened underwriting criteria. Given this drawback, a scalar approach was not chosen for this model.

An additional alternative is to use an adjusted version of the First Lien PD Model, similar to the use of the First Lien LGD model. This would reduce the Board's operational burden of maintaining two separate models covering mortgage exposures, while leveraging the similarities of the portfolios. However, this approach is not reasonable for HELOCs, which have features such as a draw period and utilization that are not accounted for in the First Lien PD Model. Without accounting for these features, the model will not be sensitive to key risks in the portfolio. For HELs, the application is more straightforward; however, the junior lien nature of these loans fundamentally alters the likelihood of default, even after accounting for other observable features. While there are costs to retaining models specific to home equity exposures, they are outweighed by the advantages of properly accounting for the individualized factors that impact loss rate projections for home equity exposures to ensure differences in firm projections accurately reflect differences in portfolio characteristics, in line with the principle of consistency and comparability from the Stress Testing Policy Statement.

v. Questions

Question D14: The Board seeks comment on whether to use any of the modeling approaches described in this section to project home equity losses, instead of the expected loss model.

E. Credit Card Model

i. Statement of Purpose

The Domestic Credit Cards Loan Loss model (referred to as the "Credit Card Model") is used to project loan losses and provisions on domestic credit card exposures to individuals that are held by firms for investment at amortized cost. Credit card exposures include general purpose and private label credit cards. General purpose cards are credit cards that can be used at a wide variety of merchants, while private label credit cards (also known as proprietary credit cards) are issued by a retailer and can only be used in that retailer's stores. Credit cards include "bank cards"—which are a type of revolving debt through which a borrower can carry a balance and continue borrowing up to a pre-defined credit limit—and "charge cards"—which generally do not have a pre-defined credit limit and must be repaid in full in each billing cycle.

During the 2008 financial crisis period in the late 2000s, annual credit card loss rates peaked at over 10 percent,[366] demonstrating the potential for credit card exposures to produce high losses during periods of economic stress. In recent stress test exercises, credit cards are responsible for the largest share of losses of any category of exposures in the supervisory stress test.[367] Furthermore, certain banking organizations subject to the supervisory stress test are highly concentrated in credit card lending. Due to the high historical loss rates of credit cards during periods of economic stress, high credit card balances among firms subject to the supervisory stress test, and the concentration of certain firms in credit card lending, producing appropriate projections of credit card losses during a hypothetical macroeconomic shock is paramount to the accuracy of the supervisory stress test.

The Board estimates the Credit Card Model using historical data on sub-portfolio (i.e., bank card or charge card), payment status and loan losses, account characteristics, and economic conditions. The model projects losses at the loan level with an expected-loss framework, as described in Section III.A of the Enhanced Transparency and Public Accountability Proposal, using data on firm-reported account characteristics from the FR Y-14M report and economic conditions defined in the Board's supervisory stress test scenarios. All firms with material

[366] "Charge-Off and Delinquency Rates on Loans and Leases at Commercial Banks." Board of Governors of the Federal Reserve System. n.d., https://www.federalreserve.gov/releases/chargeoff/chgallnsa.htm.
[367] *See*, *e.g.*, the 2025 Stress Test Results and 2024 Stress Test Results.

portfolios are required to report data on FR Y-14M, Schedule D (Credit Cards).[368] Firms with portfolio balances that are below the materiality threshold have the option of submitting or not submitting the schedule.

The expected-loss framework consists of a PD component, an LGD component, and an EAD component. Each of these components is projected using models detailed throughout this model description. TheCredit Card Model projects PD, LGD, and EAD by applying the model parameters, along with some adjustments described in this model description, to specific loans from the FR Y-14M regulatory report. TheCredit Card Model outputs projected losses under the hypothetical scenario.

ii. Model Description

The Credit Card Model projects loan losses and provisions on credit cards to individuals, including bank cards and charge cards and encompassing general purpose and private label credit cards. The Credit Card Model does not project losses on small business or corporate credit cards reported on FR Y-14M, Schedule D (Credit Card); these are modeled separately in the Other Retail Model[369] due to differences in the behavior of these credit cards compared to credit cards for individuals, and differences in business models for firms lending to business entities compared to individual consumers. The Credit Card PD Model, described in detail in Section E.ii.a, estimates the probability that an account transitions from either current or delinquent status to default status given the characteristics of the account and borrower and the unemployment rate, which is used to account for the macroeconomic environment. The Board

[368] FR Y-14M Instructions, at 4. For firms subject to category IV standards, material portfolios are defined as those with asset balances greater than $5 billion or with asset balances greater than ten percent of Tier 1 capital on average for the four quarters preceding the reporting period. For firms subject to category I, II, or III standards, material portfolios are defined as those with asset balances greater than $5 billion or asset balances greater than five percent of Tier 1 capital on average for the four quarters preceding the reporting period.
[369] *See* Section G.ii in the Other Retail Model Description.

defines bank card accounts as in default, for modeling purposes of the supervisory stress tests, if the account is five or more billing cycles (or "cycles") past due or if it is charged off. [370] The threshold of five or more cycles roughly corresponds to an account that is 120 days or more past due. This is a slightly more conservative definition of default than that of the Federal Financial Institutions Examination Council (FFIEC) Uniform Retail Credit Classification and Account Management Policy,[371] which states that "open-end retail loans that become past due 180 days from the contractual due date should be classified Loss and charged off."[372]

However, the Board observed a deterioration in the quality of data reported after accounts become seriously delinquent, reducing the reliability of the model in determining the frequency with which accounts that are five or more cycles past due proceed to 180 or more days past due. In a separate analysis, the Board tracked loans that reached five cycles past due reported in the data used for PD modeling (see Section E.ii.a for an explanation of the data source) and found that the overwhelming majority of such accounts proceeded to charge-offs. During periods of economic stress, the share of such accounts that proceeded to charge off exceeded 98 percent. Additionally, the choice of a shorter cut-off than 180 days to estimate default has been widely used across time in academic literature; for instance, Gross and Souleles (2002)[373] used a definition of default based on whether an account is three or more cycles past due, and more recently, Sengupta and Wheeler (2024)[374] defined default as 90 or more days past due. Based on

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[370] Charge card accounts are defined as in default if they are 90 or more days past due or if they are charged off. Support for the choice of charge card default definitions is available in Section E.ii.a.(2).

[371] *See* Federal Financial Institutions Examination Council. Uniform Retail Credit Classification and Account Management Policy. June 12, 2000, https://www.federalregister.gov/documents/2000/06/12/00-14704/uniform-retail-credit-classification-and-account-management-policy.

[372] Id.

[373] Gross, D. B., and N. S. Souleles. 2002. "An Empirical Analysis of Personal Bankruptcy and Delinquency," Review of Financial Studies 15: 319-347.

[374] Sengupta, Partha and Wheeler, Christopher H. 2024. "Credit Card Loss Forecasting: Some Lessons from COVID." Journal of Forecasting. John Wiley & Sons, Ltd., 43(7): 2448-2477.

this independent analysis and a review of related literature, the Board determined that using a cut-off of five cycles past due to estimate default in the Credit Card Model was appropriate to balance data quality concerns with prevailing definitions of default.

When an account defaults, it is assumed to close and cannot return to current status in the model. This assumption is consistent with the historical behavior of almost all credit cards that reach defaulted status, as described in the previous paragraph, and is aligned with the stress testing principle of conservatism.

Because the relationship between the PD and its determinants can vary with the card type, as described throughout this model description, the Board estimates separate transition models for bank cards and charge cards. This relationship also varies based on the payment status of the account and the time horizon, as described below. In particular, the Board estimates separate bank card transition models for current and active accounts; current and inactive accounts; and delinquent accounts; similarly, the Board estimates separate charge card transition models for (1) current and active accounts and (2) delinquent accounts.[375] In addition, to account for variation in the relationship between PD and its determinants by time horizon, the Board uses separate equations to model bank card transitions over the short-, medium-, and long-term; and charge card transitions over the short- and medium-to-long-term. The bank card short-term equations correspond to default in the first quarter of the projection period of the supervisory stress test; the medium-term equations correspond to the second and third quarters, and the long-term equation corresponds to the fourth through ninth quarters.[376] As described in

[375] The Board defines credit card accounts as active, for modeling purposes of the supervisory stress tests, and current if they have had activity in the past 12 months and are no more than 29 days past due; current and inactive if they have had no activity in the past 12 months and are no more than 29 days past due; and delinquent if they are between 30-119 days past due. Inactive charge cards are assumed to have zero losses.

[376] Since the model is used to project allowances as well as loan losses, and allowances are calculated based on four quarters of future losses, the long-term model is also used to project losses in the 10th through 13th projection quarters in the supervisory stress test.

Section E.ii.a.(1), the Charge Card PD Model uses a different data source than the Bank Card PD Model; therefore, historical charge card data is only available on a semi-annual, rather than quarterly basis. Due to the semi-annual frequency of the input data, the charge card equations are aligned with different time periods than the bank card equations. In particular, the short-term equations correspond to default in the first two quarters of the projection period, and the medium-to-long-term equation corresponds to default over the third and following quarters. The probability that an account defaults is modeled in an account-level, multi-period, hazard model structure,[377] and is shown in equation form in Equation E1, where each equation uses a binomial logit regression framework:

Equation E1 – Credit Card PD Model Specification

$$PD_{i,t} = f\left(X_{i,t}, Z_t\right)$$

where:

- i represents the account;
- t represents time;
- $PD_{i,t}$ represents the probability of default for account i in time t;
- $X_{i,t}$ represents loan and borrower characteristics used in the model, such as credit score and account age; and
- Z_t represents macroeconomic variables used in the model.

The Credit Card LGD Model assumes that LGD for credit cards is a fixed percentage of EAD. The assumption of a fixed LGD, rather than LGD that can vary based on account or macroeconomic characteristics, is aligned with the stress testing principle of simplicity, and is appropriate for modeling LGD given the limited historical data available, especially during periods of economic stress. Loss given default is calculated separately for bank cards and charge

[377] The model structure and potential alternatives are discussed in detail in Section E.ii.a.(4).

cards based on historical industry data on gross charge-offs and recoveries. A detailed explanation of the LGD model and its underlying assumptions is available in Section E.ii.b.

The EAD for credit cards is equal to the sum of the amount outstanding on the account at the start of the projection horizon and the estimated amount of the credit line that is likely to be drawn down by the borrower between the beginning of the projection horizon and the time of default. For bank cards, the model calculates EAD for an account that defaults at a specific time based on Equation E2:

Equation E2 – Bank Card EAD Model Specification

$$EAD_{i,t} = UPB_i + LLEQ_{i,t} * C_i$$

where:

- i represents the account;
- t represents time;
- $EAD_{i,t}$ represents the EAD for account i at time t;
- UPB_i represents the reported unpaid balance of account i at the start of the projection horizon;
- C_i represents the reported credit line of account i at the start of the projection horizon; and
- $LLEQ_{i,t}$ represents the estimated share of the credit line that is likely to be drawn down prior to default, which can be positive or negative.[378]

As shown in Equation E3, $LLEQ_{i,t}$ is estimated as a function of account and borrower characteristics, represented by $X_{i,t}$:

Equation E3 – LLEQ Model Specification

$$LLEQ_{i,t} = f\left(X_{i,t}\right)$$

[378] A positive LLEQ indicates that the borrower is projected to make additional draws between the start of the projection horizon and default. A negative LLEQ indicates that the borrower is projected to make principal payments between the start of the projection horizon and default.

Because the relationship of this factor with account and borrower characteristics can vary with the payment status of the account and time to default, the Board uses separate models to estimate the drawdown amount for current and delinquent accounts and for accounts with short-, medium-, and long-term transitions to default. The definitions of short-, medium-, and long-term in the Bank Card EAD model are slightly different than the definitions in the Bank Card PD model. In the Bank Card EAD model, the short-term equations capture loan-over-line equivalency factor ("LLEQ"), as defined in Section E.ii.c, for accounts defaulting in the first and second projection quarters; the medium-term equations capture LLEQ for accounts defaulting in the third and fourth projection quarters; and the long-term equations capture LLEQ for accounts defaulting after the fourth projection quarter. The Board adjusts estimated EAD for bank cards to exclude delinquent interest and fees based on supervisory findings that delinquent interest and fees are often reversed upon default and reflected in reduced pre-provision net revenue (PPNR) rather than as credit losses.

For charge cards, due to the smaller portfolio size and limited historical data, the Board applies a simpler model that projects EAD as a fixed percentage of the balance reported at the start of the projection period. This percentage is assigned separately for accounts that are current and accounts that are delinquent at the start of the projection period.

The model projects loss rates by applying the PD, LGD, and EAD equations to specific accounts reported on FR Y-14M, Schedule D.1 (Credit Cards). Loss rate paths are produced both for the portfolio of accounts reported on the FR Y-14M at the start of the stress test projection period (the "existing portfolio") as well as for hypothetical portfolios of new originations.[379]

[379] New originations are assumed to have the same risk characteristics as the existing portfolio, except that the account age for all accounts is reset to 0 and the delinquency status is reset to current. This ensures consistency with the supervisory stress test assumption that firm balance sheets will remain constant through the projection. See Section 2.7 of the Stress Testing Policy Statement for more information.

These loss rates are applied to the balances from the FR Y-14Q Balances schedule through the Retail Loss Aggregation process (see Section E.2.e for more information). Total loss dollars are projected as the sum of the losses on the existing portfolio plus the losses on projected new origination balances[380] during the projection period. At this stage, losses are also adjusted to reflect certain revenue and loss sharing agreements, which are agreements between firms and private entities to share a portion of both revenues and losses generated by a specific credit card portfolio (see Section E.2.e).

A detailed description of each of the model components is below. First, the structure, input data, and variables used to define the model are described. Next, support for the modeling decisions, including the model structure and the individual variables included in the model, is provided. Then, the data cleaning process and any adjustments applied to the input data are detailed. Finally, alternatives to the chosen modeling approaches are discussed, along with questions to solicit feedback from the public.

a. Probability of Default Model

(1) Description

As stated previously, the Credit Card PD Model estimates the probability that an account transitions to default in a particular quarter, given its starting payment status and account and borrower characteristics as well as macroeconomic variables; in particular, the unemployment rate. This section first describes the Bank Card PD Model; the discussion that follows includes a detailed description of how the Charge Card PD Model differs from the Bank Card PD Model.

[380] Projected new origination balances are calculated to be equivalent to the previous quarter's losses plus the projected principal payments in the previous quarter, consistent with the supervisory stress test assumption that firm balance sheets will remain constant through the projection.

To estimate the Bank Card PD model, the Board uses monthly account-level data sourced from a government agency (the "Historic Bank Cards Data") and monthly account-level data sourced from historical data reported on FR Y-14M, Schedule D (Credit Cards) (hereafter, the "FR Y-14M data"). The Historic Bank Cards Data covers many of the largest issuers of credit cards over the period from the beginning of 2008 through 2015, while the FR Y-14M data covers reporters of FR Y-14M, Schedule D from June 2012 through the present (with expanded coverage starting in 2013). Both the Historic Bank Cards Data and the FR Y-14M data include numerous and overlapping account and borrower characteristics. Additionally, accounts reported in the Historic Bank Cards Data and the FR Y-14M data are linked such that their performance can be observed continuously across the sample. The linked data and consistency in variable definitions and fields provides significant flexibility to the Board in modeling PD. Reflecting the large size of the underlying dataset, the model uses a 0.1 percent sample[381] of the joined Historic Bank Cards Data and FR Y-14M data, where the Historic Bank Cards Data are used for the period January 2008 through May 2013 and the FR Y-14M data are used from June 2013 through June 2023. Together, the combined dataset is referred to as the "Bank Cards Data."

Using the Bank Cards Data, the model defines credit card accounts, for modeling purposes of the supervisory stress test, as current and active, current and inactive, delinquent, or in default, based on account characteristics. As discussed above, the Board defines bank card accounts as in default if the account is five or more cycles past due or if it has been charged off. The Board defines bank card accounts as active and current if they have had activity in the past 12 months and are no more than one cycle past due; current and inactive if they have had no activity in the past 12 months and are no more than one cycle past due; and delinquent if they are

[381] *See* Section E.ii.a.(3) for a description of and support for the sampling process.

between two and four cycles past due. Defaulted accounts are assumed to close and cannot return to one of the other three statuses in the model; as described in the introduction to Section E.ii, this is appropriate given Board analysis of the historical Bank Cards Data from 2008 to the present that indicates that virtually all accounts that reach five or more cycles past due proceed to charge-off.

For accounts that are not already defaulted, the model projects the probability of the account transitioning to default in each quarter, given the starting payment status, using a system of nine equations. For each starting payment status, separate equations estimate the probability of default over the short-term (one quarter ahead); medium-term (two to three quarters ahead); and long-term (four to nine quarters ahead). This approach is known as a "hazard model," as it calculates the probability of the hazard (in this case, default) occurring in a given quarter, given that it has not occurred already. Mathematically, this can be denoted using Equation E4:

Equation E4 – Credit Card PD Hazard Model

$$P_{i,t} = \Pr\left[T_i = t \middle| T_i \geq t, X_{i,t}, Z_t\right]$$

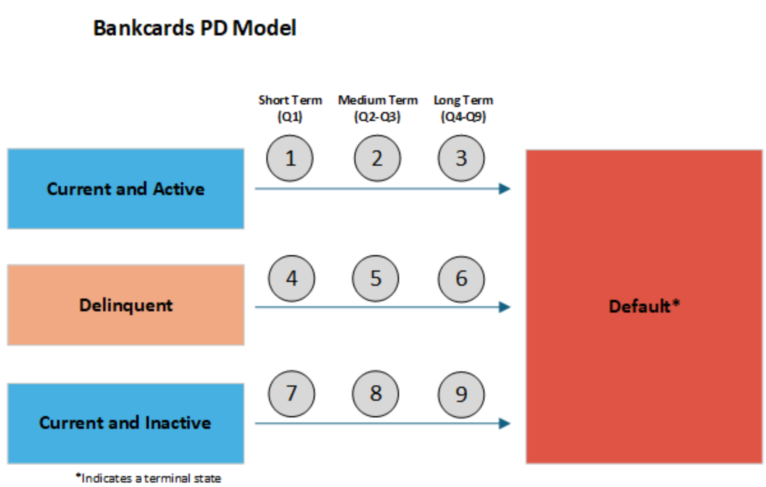
where:

- i represents the account;
- t represents time in quarters;
- $P_{i,t}$ represents the probability of default in time t, given that the account has not defaulted prior to time t;
- T_i represents the default time of an account;
- $X_{i,t}$ represents account and borrower characteristics, such as credit score and account age; and
- Z_t represents a vector of macroeconomic variables used in that equation.

One consideration is that while the models are calibrated to capture the risk of default over nine quarters, the model is applied to project losses over thirteen quarters to compute provisions as well as account losses.[382] This assumption is discussed in Section E.iii.b. To produce projections in the tenth through thirteenth projection quarters, the long-term equation is used; for the purposes of the performance period variable (defined below), it is assumed that the ninth quarter performance period coefficient is applicable to all quarters after the ninth period of the projection horizon.

The full system of equations is shown visually in Figure E1. For each of the three starting payment statuses, a separate equation is used to project the probability of default for a given quarter in the short-term, medium-term, and long-term, for a total of nine equations.

Figure E1 - Bank Card PD Model Transition Equations



Mathematically, the equations are estimated as binomial logits. A binomial logit is a model structure often used to estimate probabilities of events when the outcome is binary; in this case, either the account defaults or it does not. Given the variables in the model, each equation projects the probability of a default occurring in a quarter.

[382] The supervisory stress test produces projections of firm balance sheets over 9 quarters. An assumption in the supervisory stress test is that firms will hold an allowance covering losses over the succeeding four quarters, necessitating 13 quarters of projections to allow for the calculation of allowance levels in all 9 quarters.

The full model specification is available below; equations for current accounts are shown in Table E1; equations for delinquent accounts are shown in Table E2; and equations for inactive accounts are shown in Table E3. An explanation of the individual parameters and variable descriptions is provided below the tables; further explanation is available in Section E.ii.a.(2).[383]

[383] The referenced section also includes a detailed explanation of splines and interactions. These are statistical techniques that are used frequently in the model specification.

Table E1 - Bank Card PD Model: Current and Active Equations

Parameter	Variable Description	Current Short-Term Estimate	Current Short-Term Std. Error	Current Medium-Term Estimate	Current Medium-Term Std. Error	Current Long-Term Estimate	Current Long-Term Std. Error
1 Cycle Past Due		1.0311	0.0381	1.2447	0.0073	0.3410	0.0079
Account Age	Knot at 1 Year	0.0095	0.0041	-0.0241	0.0008	-0.0133	0.0011
	Knot at 2 Years	-0.0033	0.0083	0.0206	0.0016	0.0026	0.0015
	Knot at 3 Years	-0.0177	0.0096	-0.0034	0.0018	0.0056	0.0011
	Knot at 4 Years	0.0215	0.0107	0.0035	0.0021	-0.0004	0.0012
	Knot at 5 Years	-0.0099	0.0116	0.0007	0.0023	0.0011	0.0014
	Knot at 6 Years	0.0004	0.0124	0.0005	0.0026	-0.0008	0.0015
	Knot at 7 Years	0.0254	0.0112	0.0005	0.0025	0.0018	0.0015
Affinity Card		-0.3424	0.0633	-0.0348	0.0125	-0.0658	0.0078
Calendar Quarter	Q2	-	-	-0.1206	0.0071	-0.0862	0.0038
	Q3	-	-	-0.1365	0.0082	-0.1086	0.0040
	Q4	-	-	-0.0167	0.0069	0.0000	0.0038
Co-Branded Card		-0.1124	0.0701	0.0766	0.0122	-0.0835	0.0110
Credit Limit	Knot at $500	0.0000	0.0001	-0.0003	0.0000	-0.0002	0.0000
	Knot at $1k	0.0001	0.0001	0.0004	0.0000	0.0003	0.0000
	Knot at $2k	-0.0001	0.0000	-0.0001	0.0000	-0.0001	0.0000
	Knot at $7k	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Knot at $10k	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Credit Score	Knot at 580	-0.0371	0.0035	-0.0290	0.0007	-0.0141	0.0005
	Knot at 620	0.0298	0.0071	0.0160	0.0014	0.0025	0.0009
	Knot at 660	-0.0053	0.0063	-0.0113	0.0014	-0.0102	0.0008
	Knot at 720	0.0074	0.0044	0.0105	0.0012	-0.0001	0.0006
Credit Score x 1 Cycle Past Due	Knot at 580	0.0122	0.0021	0.0032	0.0004	0.0006	0.0004
	Knot at 620	-0.0014	0.0044	0.0000	0.0009	0.0006	0.0008
	Knot at 660	-0.0089	0.0039	0.0000	0.0009	0.0000	0.0008
	Knot at 720	0.0040	0.0028	0.0009	0.0009	0.0032	0.0008
Credit Score x Co-Branded Card	Knot at 580	0.0055	0.0034	-0.0003	0.0006	0.0007	0.0005
	Knot at 620	-0.0097	0.0066	-0.0024	0.0012	-0.0016	0.0008
	Knot at 660	0.0048	0.0053	0.0029	0.0011	0.0011	0.0007
	Knot at 720	-0.0044	0.0033	-0.0048	0.0009	-0.0054	0.0005
Credit Score x General Purpose	Knot at 580	-0.0014	0.0022	0.0045	0.0004	0.0030	0.0003
	Knot at 620	0.0123	0.0046	-0.0024	0.0009	-0.0014	0.0006
	Knot at 660	-0.0111	0.0042	0.0001	0.0009	0.0028	0.0005
	Knot at 720	0.0041	0.0031	0.0026	0.0009	0.0026	0.0005
Credit Score x Securitized	Knot at 580	0.0037	0.0023	-0.0003	0.0005	0.0002	0.0003
	Knot at 620	-0.0047	0.0046	0.0031	0.0009	0.0015	0.0006
	Knot at 660	0.0010	0.0038	-0.0001	0.0008	0.0001	0.0005
	Knot at 720	-0.0025	0.0025	-0.0049	0.0007	-0.0018	0.0004
Credit Score x Unemployment Rate	Knot at 580	0.0013	0.0005	0.0005	0.0001	0.0001	0.0001
	Knot at 620	-0.0022	0.0009	-0.0003	0.0002	0.0003	0.0001
	Knot at 660	0.0014	0.0008	0.0008	0.0002	0.0005	0.0001
	Knot at 720	-0.0013	0.0005	-0.0018	0.0001	-0.0013	0.0001
Credit Score x Unemployment Rate Change	Knot at 580	-0.0015	0.0005	0.0004	0.0001	0.0003	0.0001
	Knot at 620	0.0031	0.0010	0.0000	0.0002	0.0000	0.0001
	Knot at 660	-0.0020	0.0008	-0.0008	0.0002	-0.0007	0.0001
	Knot at 720	0.0005	0.0006	0.0005	0.0002	0.0003	0.0001
General Purpose Card		-0.1895	0.0421	-0.1176	0.0085	0.0898	0.0072
History of Delinquency		-0.1519	0.0499	0.3382	0.0087	0.1749	0.0073
Horizon	Q2	-	-	-0.0705	0.0041	-	-
	Q4	-	-	-	-	0.1010	0.0049
	Q5	-	-	-	-	0.0922	0.0049
	Q6	-	-	-	-	0.0789	0.0049
	Q7	-	-	-	-	0.0604	0.0050
	Q8	-	-	-	-	0.0299	0.0051
Intercept		-6.4007	0.0768	-3.3141	0.0174	-3.7183	0.0160
No Utilization		-1.0362	0.0503	-0.5595	0.0123	-0.2918	0.0061
Pandemic Indicator		0.1788	0.0968	0.0439	0.0224	0.0468	0.0144
Projection Quarter	Q2	0.0706	0.0279	0.0220	0.0069	0.0136	0.0038
	Q3	0.0582	0.0270	-0.0248	0.0082	-0.0061	0.0039
	Q4	-0.0118	0.0272	-0.0525	0.0074	-0.0309	0.0038
Securitized		0.1494	0.0440	-0.0105	0.0092	-0.0215	0.0076
Unemployment Rate		0.0109	0.0085	-0.0074	0.0016	0.0111	0.0013
Unemployment Rate Change		0.0409	0.0107	0.0903	0.0021	0.1142	0.0017
Unemployment Rate Change x Pandemic		-0.0264	0.0111	-0.0699	0.0025	-0.0847	0.0017
Unemployment Rate x Pandemic		-0.0453	0.0143	-0.0703	0.0034	-0.0858	0.0022
Utilization Rate	Knot at 10%	0.4085	0.1078	0.7293	0.0279	1.1769	0.0155
	Knot at 50%	0.5657	0.1815	1.3955	0.0442	-0.2532	0.0252

Table E2 - Bank Card PD Model: Delinquent Equations

		Delinquent Short-Term		Delinquent Medium-Term		Delinquent Long-Term	
Parameter	Variable Description	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
2 Cycles Past Due		-2.3873	0.0253	0.0241	0.0458	-0.1080	0.0485
3 Cycles Past Due		-1.2317	0.0235	0.0427	0.0457	-0.1652	0.0489
Account Age	Knot at 1 Year	-0.0357	0.0019	-0.0130	0.0033	-0.0130	0.0079
	Knot at 2 Years	0.0355	0.0040	-0.0002	0.0060	0.0052	0.0106
	Knot at 3 Years	-0.0001	0.0048	0.0103	0.0068	-0.0013	0.0071
	Knot at 4 Years	-0.0011	0.0056	0.0010	0.0080	0.0042	0.0077
	Knot at 5 Years	-0.0030	0.0064	-0.0068	0.0093	-0.0016	0.0090
	Knot at 6 Years	0.0017	0.0072	0.0046	0.0106	0.0041	0.0103
	Knot at 7 Years	-0.0015	0.0067	-0.0038	0.0101	0.0008	0.0097
Affinity Card		-0.3028	0.0398	-0.1068	0.0573	-0.3082	0.0626
Calendar Quarter	Q2	-	-	-0.2204	0.0293	-0.1893	0.0266
	Q3	-	-	-0.0641	0.0339	-0.1377	0.0274
	Q4	-	-	0.0741	0.0293	0.0608	0.0250
Co-Branded Card		0.2558	0.0249	-0.0072	0.0393	-0.2098	0.0470
Credit Limit	Knot at $500	0.0004	0.0000	0.0002	0.0001	0.0002	0.0001
	Knot at $1k	-0.0003	0.0001	0.0000	0.0001	-0.0001	0.0001
	Knot at $2k	0.0000	0.0000	-0.0001	0.0000	-0.0001	0.0000
	Knot at $7k	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Knot at $10k	0.0000	0.0000	0.0000	0.0001	0.0002	0.0001
Credit Score	Knot at 580	-0.0231	0.0020	-0.0183	0.0033	-0.0139	0.0036
	Knot at 620	0.0222	0.0047	0.0082	0.0084	0.0097	0.0089
	Knot at 660	-0.0064	0.0054	0.0023	0.0106	-0.0132	0.0107
	Knot at 720	0.0065	0.0054	0.0046	0.0128	0.0051	0.0124
Credit Score x 2 Cycles Past Due	Knot at 580	-0.0027	0.0013	0.0024	0.0024	0.0037	0.0027
	Knot at 620	0.0047	0.0031	-0.0039	0.0063	-0.0074	0.0067
	Knot at 660	-0.0079	0.0035	-0.0060	0.0080	0.0053	0.0083
	Knot at 720	0.0091	0.0035	0.0134	0.0095	-0.0058	0.0095
Credit Score x Co-Branded Card	Knot at 580	-0.0079	0.0017	-0.0005	0.0026	-0.0059	0.0031
	Knot at 620	0.0033	0.0039	-0.0015	0.0062	0.0140	0.0070
	Knot at 660	0.0053	0.0041	0.0019	0.0071	-0.0115	0.0073
	Knot at 720	-0.0024	0.0037	-0.0043	0.0077	0.0040	0.0073
Credit Score x General Purpose	Knot at 580	0.0139	0.0012	0.0046	0.0018	0.0024	0.0019
	Knot at 620	-0.0112	0.0029	0.0016	0.0044	-0.0003	0.0046
	Knot at 660	0.0022	0.0032	-0.0046	0.0054	0.0037	0.0054
	Knot at 720	-0.0039	0.0033	0.0029	0.0065	0.0013	0.0066
Credit Score x Securitized	Knot at 580	0.0022	0.0013	-0.0010	0.0019	0.0012	0.0020
	Knot at 620	0.0010	0.0030	0.0045	0.0046	0.0013	0.0047
	Knot at 660	-0.0017	0.0032	-0.0029	0.0054	-0.0035	0.0053
	Knot at 720	-0.0054	0.0030	0.0010	0.0060	0.0021	0.0058
Credit Score x Unemployment Rate	Knot at 580	0.0004	0.0002	0.0000	0.0004	-0.0004	0.0004
	Knot at 620	-0.0011	0.0006	0.0002	0.0009	0.0003	0.0009
	Knot at 660	0.0011	0.0007	0.0003	0.0011	0.0010	0.0011
	Knot at 720	-0.0013	0.0006	-0.0026	0.0013	-0.0013	0.0012
Credit Score x Unemployment Rate Change	Knot at 580	0.0001	0.0003	0.0003	0.0004	0.0007	0.0004
	Knot at 620	-0.0001	0.0006	0.0002	0.0010	-0.0014	0.0011
	Knot at 660	-0.0001	0.0007	-0.0007	0.0012	0.0003	0.0013
	Knot at 720	0.0004	0.0007	0.0018	0.0015	0.0000	0.0014
General Purpose Card		-0.1298	0.0163	-0.0320	0.0248	0.3167	0.0288
History of Delinquency		0.0254	0.0154	0.0672	0.0220	0.0536	0.0237
Horizon	Q2	-	-	0.1977	0.0169	-	-
	Q4	-	-	-	-	1.0431	0.0364
	Q5	-	-	-	-	0.7699	0.0375
	Q6	-	-	-	-	0.5248	0.0391
	Q7	-	-	-	-	0.2671	0.0414
	Q8	-	-	-	-	0.1691	0.0426
Intercept		1.1489	0.0437	-3.1876	0.0856	-4.3430	0.1152
No Utilization		-0.4673	0.2432	-0.1304	0.4555	0.4007	0.3081
Pandemic Indicator		-0.1249	0.0581	0.0173	0.0918	-0.1907	0.0999
Projection Quarter	Q2	0.1284	0.0163	0.0758	0.0288	0.0123	0.0273
	Q3	0.1320	0.0154	0.0408	0.0337	-0.0026	0.0268
	Q4	0.0279	0.0152	-0.0101	0.0294	0.0017	0.0256
Securitized		-0.1369	0.0189	-0.0313	0.0285	-0.0644	0.0308
Unemployment Rate		0.0128	0.0034	0.0107	0.0051	0.0310	0.0055
Unemployment Rate Change		0.0532	0.0048	0.0361	0.0072	0.0516	0.0082
Unemployment Rate Change x Pandemic		-0.0729	0.0069	-0.0455	0.0102	-0.0544	0.0110
Unemployment Rate x Pandemic		0.0079	0.0088	-0.0606	0.0136	-0.0571	0.0148
Utilization Rate	Knot at 10%	1.6213	0.0898	2.8551	0.1660	2.0937	0.1565
	Knot at 50%	-0.2989	0.1437	-1.5851	0.2464	-0.9949	0.2427

Table E3 - Bank Card PD Model: Current and Inactive Equations

Parameter	Variable Description	Inactive Short-Term Estimate	Inactive Short-Term Std. Error	Inactive Medium-Term Estimate	Inactive Medium-Term Std. Error	Inactive Long-Term Estimate	Inactive Long-Term Std. Error
Account Age	Knot at 1 Year	-0.0312	0.0248	-0.1546	0.0058	-0.0688	0.0034
	Knot at 2 Years	-0.0069	0.0502	0.1599	0.0129	-0.0117	0.0057
	Knot at 3 Years	0.1055	0.0595	-0.0028	0.0155	0.0583	0.0062
	Knot at 4 Years	-0.1459	0.0652	-0.0154	0.0174	0.0092	0.0072
	Knot at 5 Years	0.1743	0.0778	0.0252	0.0201	0.0154	0.0084
	Knot at 6 Years	-0.1169	0.0744	-0.0352	0.0225	0.0030	0.0093
	Knot at 7 Years	0.0268	0.0669	0.0358	0.0218	-0.0180	0.0086
Affinity Card		-	-	-0.2167	0.1015	-0.1763	0.0402
Calendar Quarter	Q2	-	-	0.0211	0.0541	0.0139	0.0200
	Q3	-	-	-0.0695	0.0657	-0.1025	0.0213
	Q4	-	-	0.0107	0.0558	0.0033	0.0203
Co-Branded Card		1.7031	0.1767	-0.1979	0.0444	-0.5608	0.0214
Credit Limit	Knot at $500	0.0002	0.0004	-0.0004	0.0001	0.0000	0.0001
	Knot at $1k	-0.0004	0.0006	0.0003	0.0001	0.0000	0.0001
	Knot at $2k	0.0000	0.0003	0.0000	0.0001	0.0000	0.0000
	Knot at $7k	0.0006	0.0002	0.0001	0.0001	0.0000	0.0000
	Knot at $10k	-0.0006	0.0004	-0.0001	0.0001	-0.0001	0.0000
Credit Score	Knot at 580	-0.0285	0.0072	-0.0144	0.0015	-0.0059	0.0009
	Knot at 620	0.0090	0.0149	-0.0023	0.0030	-0.0047	0.0016
	Knot at 660	0.0054	0.0128	0.0020	0.0025	-0.0016	0.0012
	Knot at 720	0.0051	0.0076	-0.0043	0.0017	-0.0111	0.0007
General Purpose Card		-0.8920	0.1675	0.3852	0.0343	0.7240	0.0171
History of Delinquency		0.0116	0.5099	0.0337	0.1245	0.1796	0.0636
Horizon	Q2	-	-	-1.0052	0.0327	-	-
	Q4	-	-	-	-	-0.4388	0.0275
	Q5	-	-	-	-	-0.2839	0.0263
	Q6	-	-	-	-	-0.1638	0.0258
	Q7	-	-	-	-	-0.1032	0.0260
	Q8	-	-	-	-	-0.0311	0.0261
Intercept		-8.2901	0.3195	-3.5613	0.0886	-3.8024	0.0522
Pandemic Indicator		0.0595	1.1861	0.1605	0.1778	0.1401	0.0854
Projection Quarter	Q2	-0.1198	0.1872	0.0680	0.0561	0.0292	0.0198
	Q3	0.0633	0.1767	0.1724	0.0653	0.0291	0.0204
	Q4	0.2338	0.1694	-0.0143	0.0593	-0.0409	0.0207
Securitized		0.1714	0.1486	-0.0861	0.0441	0.0157	0.0198
Unemployment Rate		0.2130	0.0269	0.0277	0.0073	0.0349	0.0034
Unemployment Rate Change		0.0822	0.0373	0.0511	0.0107	0.0846	0.0055
Unemployment Rate Change x Pandemic		0.0049	0.1563	0.0168	0.0204	-0.0324	0.0097
Unemployment Rate x Pandemic		-0.2257	0.1936	-0.1067	0.0278	-0.0897	0.0129

Where:

- Number of cycles past due is set to 1 if the account is that number of cycles delinquent, and 0 otherwise
- Account age is the age of the account, in months. Account age is trimmed to values between one year and eight years, meaning that accounts that are less than one year old are treated as one-year-old accounts, while accounts that are greater than eight years old are treated as eight-year-old accounts. For accounts between one and eight years old, default risk varies based on the coefficients, with spline knots[384] at annual intervals.

[384] "Spline knots" are defined in Section E.ii.a.(2).

Bounds are set at one year and eight years based on empirical analysis of the historical Bank Cards Data that showed that PD is not sensitive to changes in account age for accounts that are less than one year old; and similarly, after accounts are eight years old, the incremental impact of account aging is very small. In line with the stress testing principle of simplicity, these bounds are used.

- The terms Affinity Card and Co-Branded Card refer to different credit card product types. These values are defined based on values reported on FR Y-14M, Schedule D.1 (Credit Cards), Line Item 8 (Product Type). Affinity Cards are cards reported with a "3" ("Affinity") in this field; these are cards that have affiliations, such as with universities or unions, but that do not typically offer rewards from these organizations. Co-Branded Cards are cards reported with a "1" ("Co-brand") in this field; these are cards that are affiliated with sellers of products and services, such as retailers. For each of the variables in the above tables, the associated variables are set to 1 if the account is a given product type, or 0 otherwise. Note that co-brand cards do not include oil and gas co-brand cards (FR Y-14M product type set to "2"); the Board reviewed historical Bank Cards Data and determined that oil and gas cards may behave differently than other types of co-brand cards. Furthermore, oil and gas cards make up a tiny portion of the reported data, accounting for less than 0.5 percent of balance at all firms and less than 0.1 percent of balance industrywide. Given the small materiality of oil and gas co-brand cards, consideration of these cards is unlikely to materially impact stress test results; therefore, they are not considered.
- General Purpose Cards are credit cards that can be used at a wide variety of merchants, as reported on FR Y-14M, Schedule D.1 (Credit Cards), Line Item 7 (Credit Card Type) with the value "1" ("General Purpose"). Other cards that are not general purpose cards are "private label" cards, which are tied to the retailer issuing the card and can only be used in that retailer's stores. The general purpose card variables in the above tables are set to 1 if a card is a general purpose card, and 0 otherwise.
- Securitized is set to 1 if the account has been designated for inclusion in a master trust,[385] and is set to 0 otherwise.
- Credit limit refers to the total credit line amount available on an account. Credit limit is trimmed to values between $500 and $12,000, meaning that accounts with credit limits less than $500 are treated as if they have a $500 credit limit, while accounts with credit limits greater than $12,000 are treated as if they have a $12,000 credit limit.[386] Spline knots in between capture the varying impacts at different credit limit levels. The allowable range of $500 to $12,000 is used to account for a wide variety of credit limits while avoiding the results from being impacted by extreme outliers. Empirical analysis of the Bank Cards Data indicates that model fit is strong for credit limits outside of this range, providing further evidence that there is little incremental value in accounting for differences in default risk for accounts with credit limits above $12,000.

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[385] Credit cards are included in a master trust when they are a part of a securitization. See "Chapter II – The Securitization Transaction (Overview)." Federal Deposit Insurance Corporation. (24 May 2007), https://www.fdic.gov/credit-card-securitization-manual/chapter-ii-securitization-transaction-overview. Securitized accounts made up a majority of all bank card balances in the early portion of the data (prior to 2013) but have become less common over time. As of December 2024, just over 10 percent of accounts and just over 15 percent of balances reported on FR Y-14M, Schedule D.1 (Domestic Credit Cards) are marked as securitized.

[386] Further discussion of the allowable range of the credit limit variable is available in Section E.ii.a.(2).

- Credit score refers to the reported credit score of the borrower in a given period. Credit score is trimmed to values between 580 and 800, meaning that accounts with credit scores less than 580 are treated as if they have a credit score of 580, while accounts with credit scores greater than 800 are treated as if they have a credit score of 800. Spline knots account for the varying impacts at different credit scores at different levels. Bounds are set at 580 and 800 based on empirical analysis of the Bank Cards Data that showed that the incremental impact of credit score for accounts with scores below 580 or above 800 is very small. In line with the stress testing principle of simplicity, these bounds are used.
- Unemployment rate refers to the state-level unemployment rate in the previous quarter. The unemployment rate change refers to the year-over-year change in the state-level unemployment rate in the previous quarter. The previous quarter's value is used to reflect that there is generally a lag between economic changes and consumer responses, as borrowers may be able to rely on savings or temporary budget cuts before eventually defaulting.
- Utilization rate is the current balance divided by the current credit limit of an account. Utilization rate is trimmed to values between 10 percent and 90 percent, meaning that accounts with a utilization rate below 10 percent are treated as if they have a 10 percent utilization rate, while accounts with a utilization rate above 90 percent are treated as if they have a 90 percent utilization rate. Utilization rate is calculated as the share of the credit line drawn by a borrower in a given period. Spline knots account for the varying effects of changes at different utilization levels.
- History of delinquency is set to 1 if the account has been 60 or more days past due in the previous 3 years, and is set to 0 otherwise. This three-year lookback period is chosen based on empirical analysis that indicates that delinquency over the previous three years is associated with increased risk of future default. Therefore, a three-year window is used, even if it is longer than the two-year window generally reported by credit bureaus.
- Horizon refers to the number of quarters between the start of the projection and the date for which PD is assessed. While the short-term equations only project default over one quarter, these terms are used in the medium- and long-term equations to account for differences in default risk when looking forward by different numbers of quarters.
- Intercept refers to the intercept of the regression equation.
- No utilization is set to 1 for accounts with zero balance, and set to 0 otherwise, to reflect the differences in behavior among accounts that ended the billing cycle with zero balance.
- Pandemic indicator is set to 1 for observations where the period for which probability of default is projected is between April 2020 and December 2021, and 0 otherwise, to reflect the different behavior of accounts observed during the COVID-19 pandemic period. The pandemic indicator is justified by the substantial changes in the economic environment during the period covered by the indicator variable. Further explanation of the importance of this period is available in Section E.ii.a.(2).
- Projection quarter refers to the quarter of the start of the projection, and is used to capture seasonality effects.
- Calendar quarter refers to the quarter for which PD is being projected, to capture additional seasonality effects over the course of a calendar year.

- The “x” in the table above refers to interactions. For instance, the term “Unemployment Rate x Pandemic” is the level of unemployment rate for observations during the pandemic period, and 0 otherwise. Interactions are used to account for situations where the impact of certain variables changes as the values of other variables change.

While the Bank Card PD model uses a combination of the Historic Bank Cards Data and the FR Y-14M data, the Historic Bank Cards Data does not include information on charge cards. While FR Y-14M data does include information on charge cards, that data are only available from the beginning of the FR Y-14 collection in 2012. As a result, FR Y-14M data does not include performance history during the 2008 financial crisis period, the largest stress event in the credit card market in recent history. Accounting for this period is crucial for appropriately calibrating charge card losses under stress.

Given the lack of charge card data in the Historic Bank Cards Data during the 2008 financial crisis period, the Charge Card PD model is estimated using a separate data source. In particular, the Board uses historical account-level data from a major credit bureau (the “Charge Card Data”). The Charge Card Data is a representative sample of U.S. consumers with a credit file and social security number. The Charge Card Data includes many credit card accounts for each consumer in the panel. Charge cards are identified open accounts with entire balances due each month. Each observation includes account and borrower characteristics, including credit score, payment status,[387] origination date, credit limit, and balance. Data are available at a semi-annual frequency over most of the sample period and are available at a quarterly frequency in more recent years. The Board uses a 10 percent sample of the Charge Card Data covering the second quarter of 2004 through the fourth quarter of 2017 to fit the Charge Card PD model.[388]

[387] To mitigate the risk that the semi-annual frequency does not capture monthly payment dynamics, each observation includes the payment status of a given account for each of the previous 24 months.
[388] A discussion of the limitations of limiting the estimation data to these periods is available in Section E.iii.c.

Credit bureau data have become increasingly popular among economists in recent years, due to the breadth and depth of information contained in them. For an overview of credit bureau data, and its use cases in economic modeling, see Gibbs et al. (2025).[389]

Certain data limitations in the Charge Card Data constrain the modeling choices in the Charge Card PD Model. First, as noted in the previous paragraph, data are only reported semi-annually prior to 2017, rather than quarterly. Therefore, the Charge Card PD Model projects the probability of transitioning to default over a semi-annual period, unlike the Bank Card PD Model, which models transitions by quarter. The quarterly PD is projected to be one half of the projected semi-annual PD in each of the two quarters of a given semi-annual period. Next, the Charge Card Data include fewer variables than the Bank Cards Data, constraining the choice of variables used in the model. In addition to the above constraints that result from data limitations, charge cards generally do not have preset spending limits. As a result, two variables used in the Bank Card PD Model, credit limit amount and utilization (defined as principal balance divided by credit limit amount), are not used in the Charge Card PD Model, as they are not interpretable in the context of charge cards.

Furthermore, the quality of the Charge Card Data is less reliable after an account reaches 90 or more days past due; therefore, the model defines accounts that are 90 or more days past due (or in bankruptcy or charged off) as in default. Similar to the Bank Card PD model, this choice balances data quality concerns against industry practices as laid out in FFIEC guidance. Given the data quality concerns using data from charge cards that are more than 90 days past due, defining default based on charge cards reaching 90 or more days past due is consistent with the stress testing principle of conservatism. A threshold of 90 days past due is also consistent

[389] Gibbs, Christa, Benedict Guttman-Kenney, Donghoon Lee, Scott Nelson, Wilbert Van der Klaauw, and Jialan Wang. "Consumer credit reporting data." Journal of economic literature 63, no. 2 (2025): 598-636.

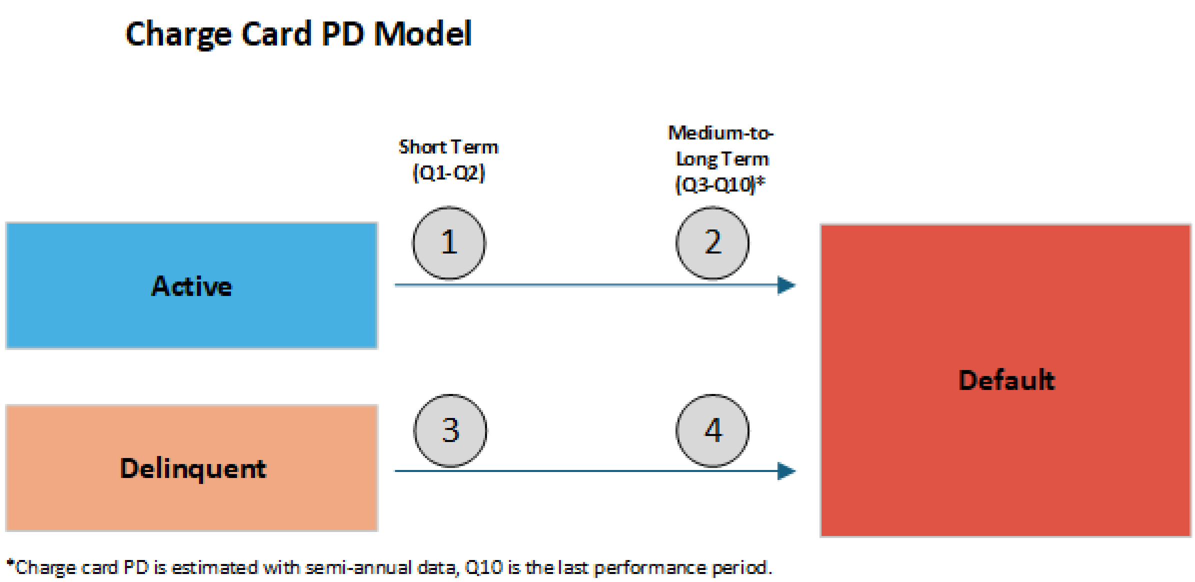
with the recommendations of Gibbs et al. (2025) for assessing delinquency using credit bureau data. Additionally, the Board reviewed historical FR Y-14M data from 2013 to the present and found that about 90 percent of accounts reaching 90 or more days past due eventually reached 180 or more days past due or charged off, suggesting that it is rare for accounts that are 90 or more days delinquent to avoid default. Finally, the number of observations and variation across charge cards is limited compared to bank cards. The limited observations are not a limitation of the Charge Card Data as much as they are a reflection of the small size of the charge card market compared to bank cards; charge cards make up less than 5 percent of accounts reported on the FR Y-14M. The smaller market size and data sample justifies a simpler approach, as the sample may not be sufficiently robust to account for additional complexity, especially in smaller market segments (for instance, inactive accounts).

Given the above, the Charge Card PD model is specified as a simpler version of the Bank Card PD model. The overall hazard model structure is maintained. However, inactive accounts are not modeled and receive zero losses.[390] Rather than model separate equations for short-, medium-, and long-term, there are only two categories for the Charge Card PD model, corresponding to short-term (the first and second projection quarters) and medium-to-long-term (the third through tenth projection quarters). Only two categories of time horizons are used due to the semi-annual data structure of the Charge Card Data, which limits the model's choice of horizons that can be used to semi-annual periods. Additionally, given the smaller size of the charge card portfolio and the semi-annual structure of the data, additional complexity is not justified; rather, a simple approach is preferred, in line with the stress testing principle of

[390] As is further explained in Section E.ii.c, charge card EAD is defined as the balance at the beginning of the projection period multiplied by a factor. Therefore, accounts with zero starting balance will be assigned zero EAD. Given that inactive accounts (which have zero balance by definition) will receive no losses regardless of PD, PD is not assigned for these accounts.

simplicity. Similarly, continuous variables are treated differently in the Charge Card PD model compared to the Bank Card PD model; see Section E.iii.a for more information. Finally, an even number of quarters is chosen for each time horizon to be consistent with the semi-annual data structure, which does not allow for the determination of more granular quarterly default rates. The equations are visualized in Figure E2. For each of the two starting payment statuses, a separate equation is used to project the probability of default for a given quarter in the short-term and medium-to-long-term, for a total of four equations.

Figure E2 - Charge Card PD Model Transition Equations



The full model specification is available in Table E4 and Table E5. An explanation of the individual parameters and variable descriptions is available in Section C.ii.a.(2).

Table E4 - Charge Card PD Model: Current Equations

Parameter	Variable Description	Current Short-Term Estimate	Current Short-Term Std. Error	Current Medium-to-Long-Term Estimate	Current Medium-to-Long-Term Std. Error
Account Age	9-18 months	0.2277	0.0557	-	-
	18-27 months	0.1972	0.0577	-0.0801	0.0326
	>27 months	-0.0362	0.0503	-0.3765	0.0290
Credit Score	581-660	-2.3479	0.0733	-1.3202	0.0439
	661-720	-4.3964	0.0963	-2.7660	0.0453
	>720	-6.8709	0.1380	-5.2704	0.0500
Credit Score x Unemployment Rate	581-660	0.0611	0.0105	0.0538	0.0061
	661-720	0.1400	0.0131	0.1234	0.0062
	>720	0.1248	0.0183	0.1740	0.0066
Credit Score x Unemployment Rate Change	581-660	-0.0478	0.0158	-0.0161	0.0091
	661-720	-0.0825	0.0196	-0.0442	0.0091
	>720	-0.0841	0.0279	-0.0630	0.0097
Default in Jul-Dec		0.0762	0.0193	-0.0158	0.0093
History of Delinquency		0.1921	0.0501	0.3081	0.0322
Horizon	H2	-	-	0.0529	0.0138
	H3	-	-	0.0356	0.0138
	H4	-	-	0.0203	0.0139
Intercept		-1.5732	0.0638	-1.9582	0.0455
Unemployment Rate		-0.0136	0.0063	0.0030	0.0048
Unemployment Rate Change		0.1511	0.0096	0.1348	0.0072

Table E5 - Charge Card PD Model: Delinquent Equations

Parameter	Variable Description	Delinquent Short-Term Estimate	Delinquent Short-Term Std. Error	Delinquent Medium-to-Long-Term Estimate	Delinquent Medium-to-Long-Term Std. Error
Account Age	9-18 months	-0.3976	0.1723	0.4285	0.1849
	18-27 months	-1.5678	0.1830	-	-
	>27 months	-1.3203	0.1677	-0.0956	0.1177
Credit Score	581-660	-2.1673	0.1975	-1.6015	0.2573
	661-720	-3.5736	0.3952	-3.4034	0.4756
	>720	-2.3045	1.2565	-5.2653	1.3550
Credit Score x Unemployment Rate	581-660	0.0968	0.0274	0.0646	0.0360
	661-720	0.0983	0.0526	0.1493	0.0623
	>720	-0.3039	0.2157	0.2317	0.1676
Credit Score x Unemployment Rate Change	581-660	-0.1327	0.0448	-0.0914	0.0534
	661-720	-0.2863	0.0909	-0.1829	0.1009
	>720	0.4424	0.2850	-0.4630	0.3096
Default in Jul-Dec		0.3366	0.0502	-0.0321	0.0637
Delinquent Status		-1.3546	0.1005	0.2282	0.1090
History of Delinquency		-0.5726	0.0996	0.1133	0.1006
Horizon	H2	-	-	1.0540	0.1068
	H3	-	-	0.6228	0.1124
	H4	-	-	0.3824	0.1182
Intercept		2.1449	0.2125	-2.7634	0.2222
Unemployment Rate		0.0226	0.0135	-0.0066	0.0180

Where:

- Account age is the age of the account, in months. Account age is categorized in the model into "less than 9 months," "9–18 months," "18–27 months," and "greater than 27 months." This grouping is discussed in Section E.ii.a.(2).
- Credit score refers to the reported credit score of the borrower in a given period. Credit scores are categorized as "580 or below," "581–660," "661–720," and "above 720." This grouping is discussed in Section E.ii.a.(2).
- Unemployment rate refers to the state-level unemployment rate in the quarter. The unemployment rate change refers to the year-over-year change in the state-level unemployment rate in the quarter.
- History of delinquency is set to 1 if the account has been 60 or more days past due in the previous 2 years, and is set to 0 otherwise. A two-year lookback window is used due to the availability of historical delinquency data reported in the Charge Card Data. However, when producing model projections, the model applies this coefficient (sets the value of this variable to "1") if the account has been 60 or more days past due in the previous 3 years. The Board believes this approach is reasonable given the finding from the Bank Card PD model that a three-year lookback window is appropriate for assessing the risk associated with previously delinquent accounts; even though accounts that were delinquent between two and three years prior are not accounted for in estimating the model parameters, it is reasonable to treat them as previously delinquent when projecting loss rates. This is consistent with the stress testing principle of conservatism from the Stress Testing Policy Statement.
- Horizon refers to the number of semi-annual periods between the start of the projection and the date for which PD is assessed. While the short-term equations only project default over one period, these terms are used in the medium-to-long-term equations to account for differences in default risk when looking forward by different numbers of periods.
- Intercept refers to the intercept of the regression equation.
- Default in second half is set to 1 if the default occurs in the second half of a calendar year, and 0 otherwise, to account for seasonality.
- Delinquency status is set to 1 in the delinquency equation if the account is 30 to 59 days past due, and set to 0 otherwise, to differentiate the default risk of accounts that are 30 to 59 days past due from those that are 60 to 89 days past due within the delinquency equation.
- The "x" in the table above refers to interactions. For instance, the term "Unemployment Rate x Pandemic" is the level of unemployment rate for observations during the pandemic period, and 0 otherwise. Interactions are used to account for situations where the impact of certain variables changes as values of other variables change.

(2) Support for Model Decisions

Review of Literature

Academic literature, as well as independent analysis, informs the development of the Credit Card PD Model. The review below includes a portion of the large body of literature relevant to credit card loss modeling.

Gross and Souleles (2002) analyze credit card delinquency and personal bankruptcy in the 1990s using panel data on credit card accounts. This is an important paper because their modeling framework has been adopted by other related papers. The authors observe account delinquency status over time. The outcome of interest is whether or not the credit card account defaults in that particular month. An account is considered in default if it is seriously delinquent, which the authors define as failing to meet payments for three consecutive monthly billing cycles. Gross and Souleles model the delinquency behavior over time of credit card accounts using multi-period probit and logit models, which can also be referred to as discrete time duration models. In these models, the probability of default is a function of origination cohort, account age, economic variables that account for the macroeconomic environment, and control variables that measure inherent risk. The effect of account age is modeled using a flexible polynomial specification to account for changing effects over time. Important predictors of default are identified as low credit score, large balances and purchases, and smaller payments; additionally, accounts have increasing default risk over the first two years after origination before declining as the account subsequently ages.

Using data from a large sample of credit card accounts over an extended timeframe that includes periods of economic expansion and recession, Agarwal and Liu (2003) provide evidence of a significant impact of unemployment on credit card delinquency. This is notable, as previous empirical studies did not consistently find a significant effect of macroeconomic factors on bankruptcy. While Gross and Souleles (2002) did not find a significant impact of unemployment on credit card default, this result can be explained by insufficient variation in the data at the time their analysis was performed. The findings of Agarwal and Liu (2003) demonstrate the importance of incorporating unemployment into the model.

Additional work in the field discusses the use of a multi-period multinomial logit model.[391] For instance, Shumway (2001)[392] makes the theoretical point that "a multi-period logit model is equivalent to a discrete-time hazard model [under certain distributional assumptions]." Sueyoshi (1995)[393] makes a similar point. Shumway's result for the multi-period multinomial logit has been applied by Agarwal, Ambrose, and Chomsisengphet (2005)[394] in a study of auto loans. Other work reviewed includes literature surveys of duration models, such as Kiefer (1988)[395], Canals-Cerda and Stern (2002)[396], and Van Den Berg (2009)[397].

Academic research clarifies the importance of accounting for the time elapsed between the start of the projection period and the projected period of default. See, for instance, Han and Hausman (1990)[398], Meyer (1990)[399], and McCall (1996)[400].

[391] "Multi-period" means the model is being used to project default in different time periods; "multinomial" means that that different possible outcomes are considered; and "logit" refers to specification of the equation.
[392] Shumway, T. 2001. "Forecasting Bankruptcy More Accurately: A Simple Hazard Model." Journal of Business, 74(1):101-124.
[393] Sueyoshi, Toshiyuki. 1995. "Production Analysis in Different Time Periods: An Application of Data Envelopment Analysis." European Journal of Operational Research Elsevier, 86 (2): 216-230.
[394] Agarwal, S., B. W. Ambrose and S. Chomsisengphet. 2005. "Asymmetric Information and the Automobile Loan Market." W.P. Office of the Comptroller of the Currency.
[395] Kiefer, N. 1988. "Economic Duration Data and Hazard Functions." Journal of Economic Literature, 26(2): 646-679.
[396] Canals-Cerda, J. and S. Stern. 2002. "Empirical Models of Search." In Search Theory and Unemployment, eds., Steven Woodbury and Carl Davidson, Kluwer Academic Publications.
[397] Van Den Berg G. J. 2009. "Duration models: Specification, Identification and Multiple Durations." Handbook of Econometrics, Chapter 55, Volume 5.
[398] Han A. and J. A. Hausman. 1990. "Flexible parametric estimation of duration and competing risk models." Journal of Applied Econometrics 5, 1–28.
[399] Meyer B. D. 1990. "Unemployment Insurance and Unemployment Spells." Econometrica 58, 757–82.
[400] McCall B. 1996. "Unemployment Insurance Rules, Joblessness, and Part-Time Work." Econometrica 64, 647–82.

The Credit Card PD Model specification incorporates the basic components that have been employed by authors in the relevant literature. Like the papers by Gross and Souleles (2002), Agarwal and Liu (2003), Agarwal, Ambrose, and Chomsisengphet (2005), and others, the PD model uses a logit specification. Advantages of this specification are the ease of interpretation of results and its ideal numerical properties.[401]

Other research has considered alternatives to the logit specification. For instance, Heckman and Singer (1986)[402] rely on a semi-parametric approach, a modeling technique that allows more flexibility in its structure.[403] A significant drawback to this type of technique is the added complexity of implementation and interpretation, as well as its numerical instability, which necessarily results in a substantial increase in model risk.[404] While semi-parametric techniques may be useful in some cases, empirical evidence does not indicate that they significantly improve loss projection under stress conditions; therefore, a logit specification is preferable. In recent years, machine learning techniques have become popular for modeling credit card performance due to the large size of the dataset and large number of available

[401] More precisely, models in the logit family have a statistical property that the estimates will always represent the optimum value, compared to other functional forms, which may produce different values depending on how the function is implemented. This is referred to as "guaranteed convergence" in technical terms. In statistical terms, models in the logit family have the property of global concavity of the likelihood function, which guarantees convergence of the maximum likelihood estimator to the optimum (Amemiya, 1985). Amemiya, T. 1985. "Advanced Econometrics," Harvard University Press.
[402] Heckman J. J. and B. Singer. 1986. "Econometric Analysis of Longitudinal Data." Handbook of Econometrics, Chapter 29, Volume 3 1689-1763.
[403] Other examples of semi-parametric techniques include Bearse, Canals-Cerda and Rilstone (2007) and Canals-Cerda and Gurmu (2007). Bearse, P., Jose J. Canals-Cerda, and P. Rilstone. 2007. "Efficient Semiparametric Estimation of Duration Models with Unobserved Heterogeneity." Econometric Theory 23 (2): 281-308.
[404] For a Monte Carlo analysis of the semi-parametric approach and a cautionary tale, see Baker and Melino (2000) and Canals-Cerda and Gurmu (2007). Baker, M. and A. Melino. 2000. "Duration Dependence and Non-Parametric Heterogeneity: A Monte Carlo Study," Journal of Econometrics 96, 357–93. Canals-Cerda, Jose and Shiferaw Gurmu. 2007. "Semiparametric Competing Risks Analysis," The Econometrics Journal, Royal Economic Society 10 (2): 193-215.

variables; for instance, see Butaru et al. (2016)[405]. Additional discussion of machine learning techniques is available in E.ii.a.(4).

Following the 2008 financial crisis, additional academic work used observed patterns over this period to provide further insights into credit card loss modeling. Banerjee and Canals-Cerdá (2012)[406] and Canals-Cerdá (2014) demonstrate a strong relationship between the macroeconomic environment and default risk, while Canals-Cerdá (2015) demonstrates that this relationship varies for different types of borrowers; in particular, prime accounts are more susceptible to changes in the macroeconomic environment compared to subprime accounts.

Finally, analysis conducted during and immediately after the COVID-19 pandemic provided additional insight into features of the market that could not be easily identified previously. Notably, Sengupta and Wheeler (2024) demonstrate that unlike during the 2008 financial crisis period, the sharp increase in the unemployment rate was not associated with an increase in credit card default. This was attributed to financial assistance provided to borrowers via government support programs during this period, which mitigated the impacts of the unemployment rate. The paper concludes that there may be value in incorporating additional macroeconomic variables in addition to unemployment rate to ensure robust model performance.

Support for Model Design

Based on the review of academic literature and independent analysis of the available data and modeling considerations, as well as the Board's experience and expertise, the Credit Card PD Model uses a hazard model to project the path of default rates over the stress test horizon. As described previously, a discrete-time hazard model is used to model the probability of an account

[405] Butaru, F., Chen, Q., Clark, B., Das, S., Lo, A., & Siddique, A. (2016). "Risk and Risk Management in the Credit Card Industry." Journal of Banking and Finance 72: 218–239. https://doi.org/10.1016/j.jbankfin.2016.07.015.
[406] Banerjee, Piu and Jose Canals-Cerdá. 2012. "Credit Risk Analysis of Credit Card Portfolios Under Economic Stress Conditions," Working Papers 12-18, Federal Reserve Bank of Philadelphia.

defaulting at a certain point, given that default has not already occurred. Given that the Credit Card Model is used to project the quarterly path of credit card losses and allowances, this is an appropriate model structure for use in the stress test. For further discussion of the hazard model and comparison with other potential model structures, see Section E.ii.a.(4).

Support for Variables and Transformations Included in the Model

With the overall model structure defined, this section discusses the variables used in the individual equations. To ensure the model is appropriately sensitive to the different indicators of default risk, the Board considered a wide range of variables for inclusion, covering characteristics of the account and the borrower as well as macroeconomic conditions. Account and borrower characteristics are sourced from the Bank Cards Data (for bank cards) and from the Charge Card Data (for charge cards) to produce the model parameters and coefficients and from the FR Y-14M report to produce PD projections. Macroeconomic conditions are based on unemployment rates[407] sourced from the Bureau of Labor Statistics. From this wide range of variables, the final variables included in each of the nine bank card and four charge card equations were chosen based on economic support, statistical fit, and, in certain cases, data availability.

In most cases, the same variables are used in each of the nine Bank Card PD equations. While it is possible that certain variables are more or less relevant depending on the starting payment status and time horizon, the Board seeks consistency where possible. Using the same variables across equations is in alignment with the stress testing principle of simplicity. This consistency improves the interpretability of the model as it reduces the number of defined variables and also simplifies the data cleaning and processing needed to run the model as it

[407] The Board considered using other macroeconomic variables as well, which are sourced from a variety of government agencies. These alternative macroeconomic variables are discussed in E.ii.a.(4).

minimizes the number of terms that must be defined. While this choice may limit the model's ability to account for cases in which a variable is only relevant in certain transitions (for instance, only for delinquent accounts, or in the long-term but not the short-term), in practice many of the same key variables impact default risk across all of the different equations.

Exceptions to this practice are made in cases in which the inclusion of a certain variable is not logically consistent, as explained below. While the same variables are generally applied to every equation for a given sub-portfolio, specifying different equations facilitates the sensitivity of the model to changes in certain variables according to starting payment status and time horizon. Notably, while indicators for performance period (the number of elapsed quarters between the start of the projection and default) are included, no such indicators are used in the bank card short-term equations, as the bank card short-term equations cover defaults for only a single quarter. Additionally, the current and inactive equations in the Bank Card PD model use slightly fewer terms than the current and active or delinquent equations. For certain variables, notably utilization, this is due to a lack of interpretability in the current and inactive equations. Utilization is not interpretable for inactive accounts because inactive accounts have zero utilization by construction.[408] For other variables, namely the interactions between product type and credit score, this is due to lack of statistical fit and economic support, as described below.

Economic support and statistical fit are used to support many of the variables included in the model. The first step of establishing economic support is to qualitatively assess, based on a survey of the relevant literature, described in "Review of Literature" and expert judgment, the most important drivers of default in the model. Relying on these factors to determine the set of variables considered for inclusion limits the risk of over-fitting, which could lead to inaccurate

[408] Utilization is calculated based on the share of available balance that is drawn by the borrower. Inactive accounts by definition have no balance drawn, so this share is uniformly zero.

projections. The Board uses this qualitative assessment to predict the relationship between a given input variable and outcome variable (in this case, the probability of an account transitioning to a different state). With that determined, a model is estimated, and based on the model estimates, it is considered whether the sign of the coefficient on the variable is consistent with predictions. If a higher value of a variable is expected to be associated with a higher probability of an account transitioning to default, the coefficient is expected to be positive; if a higher value of a variable is expected to be associated with a lower probability of an account transitioning to default, the coefficient is expected to be negative. For instance, higher credit score should be associated with lower odds of nonpayment, so the coefficient on credit score in the PD equations should be negative. If the sign of the variable in the resulting equation does not align with expectations, it is necessary to assess further and determine the reason. Additionally, if a coefficient does have the expected sign but does not have an empirically important relationship with the outcome variable, the Board may exclude the variable from the model to reduce model complexity in line with the stress test principle of simplicity.

Statistical fit is assessed based on tests of statistical significance and in-sample and out-of-sample fit. The Board tests for statistical significance via standard statistical tests, and then uses measures of in-sample and out-of-sample fit to further bolster statistical fit. The Board assesses in-sample and out-of-sample fit by using the model estimates to project default rates and then assessing whether these projected probabilities are reasonably comparable to actual probabilities. For instance, if a certain portion of accounts—such as accounts in a particular macroeconomic environment or accounts with a certain feature—are consistently assigned projected probabilities substantially above or below the actual probabilities, this would suggest that a variable is missing or poorly specified and an adjustment to the model specification could improve the quality of the model.

Variables with an interpretable economic relationship with default that enter the relevant equation with an appropriate sign, statistical significance, and sufficient magnitude—based on the Board's experience and expertise—to be economically important are included in the final model. The statistical case for including a variable is bolstered if its inclusion meaningfully improves the ability of the model to predict outcomes for a certain subset of accounts. Within a given starting status (current and active, current and inactive, and delinquent), variables are included if they meet the above criteria in at least one of the time horizon equations, even if the relationship is weaker in other equations. Including variables if they are appropriate in at least one time horizon is consistent with the stress testing principle of robustness, as it ensures models are sensitive to the underlying risks in the portfolio.

Additional factors are considered as well. Implementation feasibility is considered, as the variables applied in the model must be projected over the 13-quarter period used to produce estimates of loan losses and allowances. Simplicity is considered as well to limit operational burdens. If a more complex specification of the model (for instance, one with more variables) has a minimal impact on model performance compared to a simpler specification, based on the Board's experience and expertise, the simpler specification is used, consistent with the stress testing principle of simplicity. Finally, for situations in which the aforementioned factors of economic support, statistical fit, and implementation feasibility do not clearly point to a single specification, conservatism is considered. In cases in which two alternatives are otherwise equally preferable, the option that produces higher loss rate projections is chosen.

The above factors are generally used; however, the sign and statistical significance of terms in the model may vary by equation. In these cases, the Board relies on assessments of overall performance across equations to determine whether a variable or particular specification of a variable should be included.

Certain variables in the model use linear splines to account for non-linear effects. These non-linear effects are set at discrete locations, known as "knots," as described in Section E.ii.a.(1). These knots are identified based on Board experience and expertise, including industry knowledge and review of literature; the Board selects final knots for individual variables in individual equations based on statistical fit.

When using splines, the model balances the competing goals of simplicity and in-sample accuracy. A model with too many knots adds unnecessarily complexity and risks over-fitting the data and creating spurious or volatile relationships, while a model with too few knots will fail to account for meaningful variation in the relationship between the variable and default risk. To appropriately balance these concerns, the Board tested specifications with different placements of knots, chosen both based on distributions of the input data and expert judgment. Segments with similar slopes or that were based on sparse data were combined until the Board determined that further eliminating knots would lead to a meaningful loss of predictive power, while additional knots were added in cases in which the Board observed poor performance at particular values of the variable.

A final consideration when using splines is the treatment of observations at the tails of the distribution. For most variables, most observations of a given variable will fall within a certain limited range, usually, but not always, in the middle of all possible values. However, a small number of observations will fall in "tail" regions that are further away, closer to the highest or lowest possible values. Some continuous variables, such as credit limit, are theoretically unbounded, and can take any value above zero. Because of the sparseness of observations, it is challenging to determine the true impact of a change in a variable on default risk at these tails. To minimize the impact of outliers at the tails, the model imposes flat impacts for values below the first and above the last spline knot. This "flatness" is implemented by trimming the extreme values of a variable. For instance, for credit limit, flatness is imposed below $500 and above $12,000; in practice, this means that accounts with credit limits below $500 are treated as if the credit limit is $500, while accounts with credit limits above $12,000 are treated as if they have a credit limit of $12,000. These first and last knots were selected to capture a wide range of the distribution, leaving a small share of observations for which this flatness constraint applies.

When the impact of one variable on default depends on the value of a different variable, an "interaction" is used. Mathematically, an interaction is specified as the product of the two variables. For instance, while higher unemployment rates are associated with higher default rates for all borrowers, this impact is magnified for prime (higher credit score) borrowers. An interaction between the unemployment rate and the borrower credit score allows the model to account for this elevated sensitivity among prime borrowers.

In addition to using account and borrower characteristics, the model accounts for the macroeconomic environment through the use of the unemployment rate. Specifically, the model is estimated using the state-level unemployment rate, with state defined based on the address of the borrower. The unemployment rate is used to proxy for household labor market conditions; incorporating state-level data accounts for variation in the economic environment across geography. When the unemployment rate is increasing or elevated, borrowers are likely to have income or liquidity shocks, reducing their ability to make payments on their credit card accounts.

Analysis of historical non-payment and assessment of statistical fit of the model indicates that the credit card default risk is sensitive to both the contemporaneous level of the unemployment rate and changes to the unemployment rate; in other words, borrowers are more likely to default when unemployment is high and also are more likely to default when unemployment is increasing, regardless of its level. Specifically, the year-over-year change in the unemployment rate is used, as using the year-over-year change (as opposed to the change over a shorter period) ensures that any impact from these variables is driven by real changes in the macroeconomic environment rather than short-lived trends or outlier values of reported unemployment rates. Other macroeconomic variables were considered as well but ultimately not included in the model; a full discussion of alternative macroeconomic variables is available in Section E.ii.a.(4).

The rest of this section discusses how the above principles are applied to define each of the variables used in the model. A further discussion of alternative variables not included in the model is available in Section E.ii.a.(4).

Bank Card

- Cycles past due: Equations are estimated separately for current and active, current and inactive, and delinquent accounts; however, there is variation in delinquency within these categories. For instance, current and active accounts can be truly current or one cycle past due, as accounts are generally not reported delinquent to credit bureaus until they reach a full cycle past due (or, alternatively stated, have reached their second cycle past due); accounts that have missed a payment are more likely to default than accounts that have not. Similarly, delinquent accounts are more likely to default as the severity of the delinquency, as judged by the number of cycles past due an account is, increases.
- Age of account: As noted in the review of literature earlier in this section, academic literature has shown that default risk varies for accounts of different ages. While the direction of the impact varies by equation, in general, newer accounts are riskier than more seasoned accounts. Spline knots are used to account for the fact that the impacts of seasoning are generally stronger for newer accounts before flattening out over time.
- Horizon: For the medium- and long-term equations that cover multiple periods, variables are used to assess different levels of risk as the horizon increases. In general, delinquent accounts have lower default risk as the horizon increases, as accounts that do not default immediately are more likely to have cured. For current and active accounts, the risk peaks after a few quarters. For current and inactive accounts, the risk increases over

time, as it becomes more likely over time that inactive accounts will become active, draw a balance, and default.

- Calendar quarter of projection period start: Credit card delinquency and default is highly seasonal due to differences in consumer balance sheets over the course of the year. This is observable in the Bank Cards Data and has also been recognized in other sources, such as Barnes, Bopst, and Driscoll (2025).[409] This term accounts for these seasonal differences in starting position.
- Calendar quarter of projected default: As noted directly above, credit card delinquency and default is highly seasonal due to differences in consumer balance sheets over the course of the year. This term also accounts for these seasonal differences in borrowers' default positions.
- Previous delinquency: Among current accounts, accounts with a history of delinquency are more likely to default in the future than accounts that have never been delinquent. Among delinquent accounts, accounts that have previously been delinquent are less likely to default, as a history of delinquency shows that the borrower has a history of becoming delinquent without reaching default.
- Credit limit amount: Default risk varies based on the amount of the credit line. This effect varies at different credit limits; splines are used to capture this variation.
- Utilization: Higher utilization rates are associated with increased risk of default, as they suggest that borrower liquidity is constrained. This effect varies at different utilization levels; splines are used to capture this variation.
- No utilization flag: There is a notable decrease in default risk for accounts with zero balances, even compared to those with low (but non-zero) utilization.[410]
- Credit score: Credit score is an indication of a borrower's likelihood of becoming delinquent; given this, credit score is a key factor in the model. In general, borrowers with higher credit scores are less likely to default than borrowers with a lower credit score. This effect varies at different credit score ranges; splines are used to capture this variation. The spline knots are set based on cut-off points that are common in academic and government sources,[411] with flatness imposed (as described earlier in this section) for

[409] *See* Barnes, Kayleigh, Connor Bopst, and John Driscoll (2025). "Predicting Credit Card Delinquency Rates," FEDS Notes. Washington: Board of Governors of the Federal Reserve System, February 28, 2025, https://doi.org/10.17016/2380-7172.3732.
[410] Accounts with zero utilized balance are still considered in the Credit Card PD Model, as at the start of the projection period they still have access to their credit lines, and can draw down the balance between the start of the projection period and default.
[411] *See* "Borrower Risk Profiles." Consumer Financial Protection Bureau. https://www.consumerfinance.gov/data-research/consumer-credit-trends/student-loans/borrower-risk-profiles/; and Brown, A., & S. McAlister. "Office of Research Blog: Credit Score Transitions During the COVID-19 Pandemic." 25 Jan 2023, https://www.consumerfinance.gov/about-us/blog/office-of-research-blog-credit-score-transitions-during-the-covid-19-pandemic/.
These knot locations are also similar to cut-off points that have also been documented in the literature (albeit, often for mortgage lending). A cutoff at 620 has commonly been used in mortgage lending since the 1990s (Keys, Mukherjee, Seru, & Vig, 2010 and citations therein). Bubb & Kaufman (2014) show evidence for important cutoffs at both 620 and 660. Laufer & Paciorek (2022) discuss the history of credit scoring thresholds and note that the Federal Housing Administration has a cutoff at 580 for borrowers making down payments of less than 10 percent. Agarwal, Chomsisengphet, Mahoney, & Stroebel (2018) documents notable credit score discontinuities in credit card lending at scores of 660, 700, 720, 740, and 760. Most recently, Agarwal, Presbitero, Silva, & Wix (2023) uses cutoffs at 660, 720, and 780.

credit scores above 800 to reflect that there is little further decrease in default risk above this value, based on Board analysis of historical Bank Cards Data. Since the impact of many other risk factors varies across borrowers with different credit scores (see Canals-Cerdá 2015), credit score is interacted with many other features. Due to limited sensitivity in the current and inactive equations, some of these interactions are excluded. The terms with which credit score is interacted are listed below:

- Product type
- Delinquency status (number of cycles past due)
- Whether the account is securitized or included in a master trust
- Unemployment rate
- Unemployment rate change

- Product type (affinity, co-brand): Default risk is generally lower for affinity or co-brand cards compared to other cards, although the differences in coefficients demonstrate that the impact varies by equation. The lower default risk for these cards may reflect the different population and behavior of borrowers to whom affinity and co-brand cards appeal. See, for instance, Bakhtiari, Murthi, and Steffes (2013)[412].
- General purpose: Because general purpose cards can be used at a variety of merchants rather than only at the stores of the retailer issuing the card, these cards may behave differently than other cards.
- Securitized flag: Accounts held in a master trust may behave differently than other cards due to potential differences in account management (e.g., in managing modification terms) for these accounts to comply with the terms of the trust.
- Unemployment rate: Both the level of unemployment rate and the year-over-year change in unemployment rate are included to account for the increased risk of default both as unemployment levels rise and when it is high. These terms account for the role of the macroeconomic environment in determining default risk. As previously noted, the unemployment rate variables rely on levels or changes in the previous quarter to account for the lag between when the economy declines and when borrowers run out of savings to pay their credit cards.
- Pandemic Indicator: During the COVID-19 pandemic, default rates remained low while unemployment rates spiked, counter to the historical trend. The pandemic indicator accounts for the breakdown in historical relationships that was observed during this period, due to government support programs that were made available to individuals during this period. The pandemic indicator is also interacted with unemployment rate levels and changes to account for the specific breakdown of the relationship between the unemployment rate and default during the pandemic.

[412] Bakhtiari, A., Murthi, B. P. S., & Steffes, E. (2013). "Evaluating the Effect of Affinity Card Programs on Customer Profitability Using Propensity Score Matching." Journal of Interactive Marketing, 27(2), 83-97.

Charge Card

Given the smaller size of the charge card portfolio compared to the bank card portfolio, the charge card model uses a simpler specification focused on the most important determinants of default.

- Age of account: This variable is divided into categories according to age ranges: less than 9 months old; between 9 and 18 months old; between 18 and 27 months old; and greater than 27 months old. The coefficients on these variables show that generally, the probability of default declines as the account becomes more seasoned, as with bank cards. The differences in the coefficients across categories demonstrate the value in treating accounts with these different ages differently; including additional age categories was considered but was ultimately not chosen to align with the principle of simplicity from the Stress Testing Policy Statement, as the Board determined that including additional age categories would not sufficiently improve model performance to justify the increase in complexity.
- Seasonality: Similar to bank cards, and as supported in the discussion of seasonality in the bank card model, default among charge cards is highly seasonal; the statistically significant coefficients on the charge card seasonality variables confirm that seasonality is also relevant for predicting charge card defaults. Since only semi-annual performance is observed, the model accounts for the likelihood of default in the second half compared to the first half of the year.
- Performance period (medium-to-long-term equation only): For the medium-to-long-term equations that cover multiple periods, variables are used to assess different levels of risk as the horizon increases. In general, delinquent accounts have lower default risk as the horizon increases, as accounts that do not default immediately are more likely to have cured. For current accounts, the risk peaks after a few quarters.
- Previous delinquency: Similar to bank cards, among current accounts, accounts with a history of delinquency are more likely to default in the future than accounts that have never been delinquent. Among delinquent accounts, accounts that have previously been delinquent are less likely to default in the short-term, as a history of delinquency shows that the borrower has a history of becoming delinquent without reaching default, although this effect is less notable over the medium-to-long-term.
- Credit score: This variable is categorized into bins for less than 580, 580–660, 660–720, and over 720. These bins use cut-offs similar to the Bank Card PD Model's cut-offs, except that a single category covers accounts with credit scores between 580 and 660, rather than two categories. These two categories are combined in the Charge Card PD Model due to data sparseness, as the charge card borrower population is smaller than that of bank cards, and fewer borrowers have credit scores below 660. This is aligned with the principle of robustness from the Stress Testing Policy Statement. With the categories determined, the coefficients on the credit score categories show that as credit score increases, default risk declines, as expected. Similar to bank cards, and consistent with

the literature,[413] accounts of borrowers with higher credit scores are more susceptible to macroeconomic environment changes. An interaction between credit score and both the level and change in unemployment rate is applied to capture this effect.

- Unemployment rate: Both the level of the unemployment rate and the year-over-year change in unemployment rate are included to account for the increased risk of default both as unemployment levels rise and when unemployment is high. These terms account for the role of the macroeconomic environment in determining default risk.
- Level of delinquency: The delinquent equations are used to project default for accounts that are 30–89 days past due. The model accounts for the increased probability of default for accounts that are 60–89 days past due (compared to 30–59 days past due) with an indicator variable to differentiate accounts based on how severe the delinquency is. As accounts that are two months delinquent have missed an additional payment compared to accounts that are one month delinquent, they are less likely to cure going forward.

(3) Adjustments and Data Cleaning Steps

The Board makes several adjustments to ensure the estimation of the model is based on representative data and is minimally impacted by errors or outliers. These adjustments are described in detail in this section.

Estimation Sampling and Loan Inclusion

Bank Card

As previously stated, the Bank Card PD model uses a 0.1 percent sample of the Bank Cards Data, covering the period from the beginning of 2008 through June 2023. To randomly sample the data, the Board assigns a random value to all accounts in the data, and filters to random values covering one out of every 1000 accounts. Despite the small share of the total data used to estimate the model parameters, the large size of the underlying dataset ensures that 0.1 percent remains a sufficiently large sample to produce reliable estimates of model parameters.

Of this 0.1 percent sample, further refinements are made to ensure the estimation data are representative of the data on which the model parameters are applied. First, charge cards and small-business and corporate credit cards are removed from the sample. As noted previously,

[413] *See*, *e.g.*, Canals-Cerdá (2015).

charge card data were not available during the 2008 financial crisis period; given this constraint, the Board instead produces Charge Card PD model parameters using the Charge Card Data. Small-business and corporate cards are removed because these accounts are modeled separately within the Other Retail Model.

Next, accounts are excluded if they are missing key variables necessary for modeling. This includes accounts missing delinquency status, borrower state[414] (since unemployment rate is assigned at the state level), refreshed credit score,[415] origination date (used to calculate account age), balance, or credit limit. When these fields are missing, it is impossible to assign values to certain variables needed for modeling; therefore, they are excluded from the estimation sample. Similarly, accounts missing information needed to determine whether they are active or inactive are removed. Accounts with a reported credit limit of zero are also excluded, as the model is unable to define utilization for accounts with zero credit limit.

Certain other filters are added for representativeness, reasonableness, and consistency, as follows. The Board removed from the sample a handful of firms that historically reported the Bank Cards Data for a short period of time, but no longer report the data due to no longer meeting the criteria for reporting FR Y-14M, Schedule D.[416] In particular, firms are included in the panel only if a full, consecutive year of data was reported by that firm at any point starting in or after June 2013. This condition is applied because the Board uses the path of key variables

[414] Only accounts in the 50 U.S. states and Washington, DC are modeled. In most cases, domestic credit card balances exclude loans to borrowers in U.S. territories. *See* FR Y-9C instructions at 391, glossary entry for "Domestic Office." Less than one percent of portfolio balance as of December 2024 is associated with accounts reported in U.S. territories.

[415] If the account is less than two years old and the refreshed credit score is missing, the origination credit score is applied instead of dropping the account. This approach is discussed in "Estimation Data Cleaning and Preparation." Additionally, after the data cleaning described in "Estimation Data Cleaning and Preparation," credit scores below 325 or above 900 are considered invalid, as they are either extremely unusual in practice or well outside of the established score range of the most popular credit ratings bureaus. Accounts with credit scores outside of this range are removed along with accounts with missing credit scores.

[416] *See* FR Y-14M instructions for reporting criteria.

over time to assess data quality. The Board determined that, where there is only a short panel of data to inspect, it would be difficult to ensure reported data were sufficiently accurate.[417] Next, accounts that have reached default or closed status are not modeled following the default date, as such accounts cannot generate future losses.[418]

To test whether there were sufficient observations for use in modeling even after filtering, the Board applied the model framework to different 0.1 percent sub-samples and confirmed that they were within a reasonable level of tolerance. Based on this finding, the Board determined that the sample is sufficient for use in modeling even the sparser segments in the model.

Charge Card

As previously stated, the Charge Card PD model is estimated based on a 10 percent sample of the Charge Card Data, which is itself a representative sample of the U.S. population with a credit file and social security number. The 10 percent sample was chosen, as opposed to the 0.1 percent used for bank cards, due to the smaller size of the charge card market.[419] The Board determined that 10 percent of charge cards reported in the Charge Card Data provided sufficient coverage of the market while reducing computational constraints when using additional data given the finding of coefficient stability, as described below.

First, the Charge Card Data relies on a source that includes both bank cards and charge cards. To limit the sample to charge cards, only open accounts with entire balances due each month are included. Additional filters to the charge card estimation data are described below.

[417] If only a subset of a firm's data is available in a given period, the Board will remove that firm's data from that period in the Bank Cards Data to mitigate the risk that it was incomplete. Incomplete data may pose representativeness concerns when certain accounts are not reported.
[418] Accounts are generally treated as "closed" based on how they are reported as of month-end, except that in the Historic Bank Cards Data, the Board identified data quality issues in how certain firms reported month-end closed status. For these reporters, cycle-end closed status is used instead. Since account closure is generally permanent, the difference between these definitions is, in practice, small.
[419] As of December 2024, less than 2 percent of accounts and less than 5 percent of the balance of credit cards to individuals, as reported on FR Y-14M, Schedule D (Credit Cards), was made up of charge cards.

Similar to bank cards, accounts that have reached default are not modeled after the default date, as defaulted accounts will not generate additional losses. Additionally, accounts are not included if their performance cannot be tracked over the succeeding five semi-annual periods;[420] without such information, the probability of default over the projection period cannot be assessed.

Similarly to bank cards, the Board determined that after the filters were applied, based on assessments of estimated coefficients on different sub-samples of the data, that the sample size is sufficiently large that it is not substantially affected by sampling bias and sufficient accounts remained in the sample to reliably model the portfolio.

Estimation Data Cleaning and Preparation

With the estimation sample defined, the next step is to clean and prepare the data used to estimate the model parameters. This section first discusses data cleaning steps that are applied to both bank and charge cards; specific data cleaning required for the individual sub-portfolios is laid out in the succeeding sub-sections.

One variable that is common to both bank card and charge card data is the state-level unemployment rate. The historical, seasonally adjusted state-level unemployment rate is sourced from the Bureau of Labor Statistics. Based on the state as reported in the cardholder's billing address,[421] the state-level unemployment rate in a given quarter (or a given semi-annual period, in the case of the Charge Card PD model) is assigned to the account in that quarter.[422]

[420] *See* "Estimation Data Cleaning and Preparation" for caveats; in particular, in certain cases, described in that section, the Board assumes accounts that stop being reported have defaulted based on other characteristics reported in the Charge Card Data.
[421] The state of the primary borrower is used in cases in which there are multiple cardholders on one account.
[422] Specifically, the Bank Card PD Model uses the average value over the three months of the quarter, while the Charge Card PD Model uses the average value over the three months of the second quarter of the semi-annual period.

Additionally, for estimation of the medium- and long-term equations (medium-to-long-term in the Charge Card PD model), including accounts that defaulted prior to the beginning of the horizon used in that equation would introduce bias into the model. Therefore, accounts that default in the first quarter are removed from the sample used to estimate the medium-term equations in the Bank Card PD model, and accounts that default in the first three quarters are removed from the sample used to estimate the long-term equation in the Bank Card PD model; similarly, accounts that default in the first semi-annual period are removed from the sample used to estimate the medium-to-long-term equation in the Charge Card PD Model.

Finally, the account age variable is dynamically updated in each projection period to reflect that accounts continue to become more seasoned over the projection period. For instance, when projecting the probability of default in the sixth projection period for a bank card that is 18 months old at the start of the projection, the model treats the observation as if it is 36 months old (18 months to start plus 18 months to cover the six quarters that have elapsed). This process is common to bank cards and charge cards, with the caveat that age is updated dynamically in six month increments for charge cards, given the semi-annual frequency of the Charge Card PD Model.

Bank Card

First, borrower credit score is a fundamentally important variable for projecting the likelihood of default. Borrowers with high credit scores consistently default at lower rates than borrowers with low credit scores.[423] However, the bank card estimation data include accounts with borrower credit scores from a variety of vendors; within a given vendor, many different

[423] This finding has been observed in academic literature for a long time; see, for instance Agarwal and Liu (2003). The Board reviewed Bank Cards Data and found relationships between credit score and default risk observed in academic literature can be replicated in this dataset as well.

versions of a credit score may be available. A given credit score value may not reflect the same level of default risk across different vendors or different versions of scores.

Most credit scores reported in the Bank Cards Data range from a minimum score of 300 to a maximum score of 850. Since this score range is most common, the Board uses this range to estimate the coefficients used in the Bank Card PD model. For credit scores with a 300–850 range or a reasonably similar range, the Board does not make any adjustment, implicitly assuming that a given value represents the same level of default risk regardless of the credit score vendor and version. For instance, in one case in which a credit score version used a slightly wider range, the Board determined that the range used by this version was similar enough to the 300–850 range so as not to require an adjustment. One mitigating factor is that the Bank Card PD model applies the same level of projected PD to all bank cards with credit scores below 580 or above 800, assuming other variables are constant. This reduces the concern that an out-of-range score could be assigned inappropriately high or low PD projections. However, in specific cases in which credit scores use a substantially different range from the 300–850 range, the Board relies on supervisory data, reviewed by the Board, to align these scores with the 300–850 range. The same adjustment is made when fitting the model parameters and when using the model parameters to project PD in the supervisory stress test.

Next, recently originated accounts do not have a reported refreshed credit score available are adjusted. Refreshed credit score is needed to ensure the model is reflective of contemporaneous characteristics of the borrower. These scores are often missing for recently originated accounts, likely because the credit score has not been refreshed since origination. To avoid inappropriately excluding new accounts and potentially biasing the sample, the Board instead applies the origination credit score when the refreshed credit score is unavailable, in cases where the account is less than 24 months old.[424] If the account is more than 24 months old or the origination credit score and the refreshed credit score are both missing, the account is instead dropped from the sample.

An additional adjustment is made to account for variation in reporting balances in the historical data. As previously noted, contemporaneous principal balance is used to calculate utilization. However, contemporaneous principal balance is reported in two ways in the FR Y-14M data, as both the balance at the end of the billing cycle and balance at the end of the month are reported.[425] Cycle-ending balance and month ending balance are similar on average; while some borrowers make payments between the end date of the cycle and the end of the month, other borrowers make additional purchases. While payments and additional purchases may likely be dependent on the date the cycle ends within a month, the Board has assessed based on supervisory data that most firms distribute the cycle-end dates widely over the month; as a result, month-end balances are not on average impacted by the elapsed time between the cycle-end and the month-end. Nevertheless, because historical data mostly uses cycle-ending balance, the cycle-ending balance is used throughout the model wherever possible. Furthermore, independent of differences in data availability, the Board believes cycle-ending balance is a better indicator of balance because it is unaffected by the number of days between the end of the cycle and the end of the month for each account, which can affect the number of additional purchases and payments that can be made after the end of a cycle. For this reason, cycle-ending balance

[424] The Board determined to use a 24-month threshold based on its experience and expertise, supported by a review of historical Bank Cards Data. The historical Bank Cards Data show that generally, refreshed credit score changes minimally over the first two years after opening an account. After two years, the origination credit score is a less effective proxy for refreshed credit score; meanwhile, for accounts where a refreshed credit score is still missing after this point, this is likely due to true missing data rather than insufficient time having passed for the score to have refreshed.

[425] In the FR Y-14M data prior to March 2018, the instructions required firms to report cycle ending balance unless it was unavailable, and month ending balance otherwise. Starting in March 2018, the two variables began to be included separately.

provides a more consistent comparison across accounts and across firms than month-ending balance. However, as stated above, while cycle-ending balance is more appropriate, month-ending balance is similar on average. Therefore, in cases in which cycle-ending balance is not available, month-ending balance is used instead. The decision to use month-ending balance when cycle-ending balance is unavailable avoids introducing any bias into the model if accounts where cycle-ending balance is unavailable differ from other accounts in meaningful ways, and avoids further reducing the sample, by removing accounts missing cycle-ending balance.

Similarly, both delinquency at the end of the cycle and delinquency at the end of the month are reported on the FR Y-14M; similar to the process for principal balance, cycle-end delinquency status values are used wherever possible. This is consistent with the explanation in the previous paragraph; namely, that using values as of cycle-end is more consistent and comparable than values at month-end.[426] In cases in which cycle-end delinquency status is unavailable, month-end delinquency is used instead. While month-end delinquency is an imperfect proxy for cycle-end delinquency, these values generally align, and month-end delinquency provides the best available assessment of delinquency for accounts that do not have delinquency status reported as of cycle-end. To use as much available data as possible, the Board determined that it was appropriate to use month-end delinquency in these cases, rather than removing the observations entirely.

Finally, the Board has identified circumstances in which certain reporters in the historical data reported changes to the credit limit when the credit limit had not in fact changed. This appears to have occurred especially for delinquent accounts, as well as current accounts with balances above the previously-reported credit limit. The Board flags problematic changes to the

[426] In particular, evaluating delinquency as of month-end gives accounts additional time to cure between the end of the cycle and the end of the month.

credit limit when the credit limit reported for an account is different than its previous month's value, even though the firm did not report a change in the credit line for that account based on FR Y-14M, Schedule D.1, Line Item 47 ("Line increase or decrease in the current month"). While the Board generally attempts to receive resubmissions of historical data with data quality issues, in the identified cases, due to the amount of elapsed time since these inappropriate credit limits were reported, a resubmission of the misreported data is not feasible. In general, the Board uses reported data as given and adjusts reported data only in limited circumstances and following confirmation with the firm that the reported historical data was erroneous. In situations in which the Board confirms with the firm that a high level of current credit limits were reported erroneously, and resubmission of the misreported data is not possible, the Board makes an adjustment to the data to assume that all accounts in that period for that firm that are not marked as having their credit line increased or decreased have a credit limit equal to the value reported immediately prior to the first time the credit limit inappropriately changed. This adjustment is appropriate because based on the lack of a reported credit line change, the true credit line of the account should be its value prior to the first date the reporting error is identified. Because of the importance of credit limit and utilization to credit card modeling, this adjustment helps ensure that coefficients are calibrated properly.

Charge Card

A handful of adjustments are made to clean the Charge Card Data prior to using the dataset to calibrate the modeling coefficients. First, in certain cases in which the credit score in a given period is missing, the previous value is used instead as a proxy. Next, the model adjusts for accounts that disappear from the Charge Card Data in a given quarter. When accounts default, they often are no longer reported; therefore, ignoring accounts that exit the sample could bias the estimated default rates downward. To account for this, the model uses other information to impute default when accounts stop being reported.[427] Specifically, default is imputed if an account disappears from the dataset if both of the following conditions are triggered:

- The consumer-level data indicates that the consumer has had at least one credit card account 90 or more days past due in the previous six months and at least one credit card account with a "major derogatory event" (charge-off, bankruptcy, or internal collection) in the previous 24 months.
- The credit score reported for the consumer is less than 600. Since credit scores account for the payment history of the borrower, a credit score of less than 600 is often reflective of a recent default. This assumption is similar to that used in the Auto Model,[428] except that compared to the credit score threshold of 540 used in the Auto Model, a higher threshold was used for the Charge Card PD model. This higher threshold is reflective of the fact that consumers tend to prioritize making payments on auto loans and other forms of secured lending above credit cards;[429] as a result, borrowers with defaulted credit cards may in some cases retain higher credit scores even after default compared to borrowers with defaulted auto loans.

If an account disappears, and at least one of the above conditions is not triggered, the model assumes that no default occurred. Instead, in these cases, accounts are dropped as described above in "Estimation Sampling and Loan Inclusion," as future performance is not observable.

Projection Data Cleaning and Preparation

The estimated Bank Card and Charge Card PD Model parameters are applied to data reported on FR Y-14M, Schedule D (Credit Cards) at the start of the projection period of each supervisory stress test exercise to project the probability of default of each account in the portfolio. This section discusses the data cleaning steps needed to produce model projections.

[427] Since the data are sourced from a major credit bureau, the Charge Card Data can be linked to other information about the credit history of an individual.
[428] *See* Section F.ii.a.(3) in the Auto Model Description.
[429] For instance, see Exhibit 9 here: Hughes et al. "How Resuming Student Loan Payments Will Affect Consumer Credit Risk." Nov 2023, https://media-publications.bcg.com/How-Resuming-Student-Loan-Payments-Will-Affect-Consumer-Credit-Risk.pdf.

Since the Bank Card PD Model and the Charge Card PD Model use the same data sources for producing model projections, the data cleaning process is similar across the two sub-portfolios. Similarly, since the data used for model projections relies on the same source as the Bank Card PD model estimation data, many of the data cleaning steps align with those used to clean the Bank Card PD estimation data. Additional data cleaning considerations that are relevant or necessary only when using the model to project losses are described in this section.

First, the projection data are sampled to account for the extremely large number of credit card accounts included in the FR Y-14M data. Specifically, for firms with credit card accounts (bank card and charge card) surpassing $10 billion in overall balance, a 10 percent sample of the accounts reported at the start of the projection period is used. For firms with less than $10 billion in balance, all accounts reported at the start of the projection period are used. The $10 billion cut-off is chosen to ensure that a sufficiently large number of accounts are included for each bank to produce a reliable projection of losses under the hypothetical scenario. For firms with large credit card portfolios, the Board compares the distribution of key variables[430] used in modeling among the 10 percent sample with the entire population of reported accounts to ensure representativeness; in all cases to date, the sample has been representative of the full population. Additionally, for all firms for which a 10 percent sample is applied, the Board has confirmed that the sample of accounts used in projections exceeds 1 million observations; statistically, with a sample this large, the likelihood that the loss projections produced for the sample would differ substantially from the loss projections for the whole population of accounts is vanishingly small.

[430] Key variables include balance, credit limit, credit score, delinquency status, previous delinquency status, actual payment amount, purchase volume, current interest rate, account age, state, active or closed status, charge-off reason, product type, and securitized flag. These variables are chosen based on the Board's judgment and expertise, to capture a range of factors (including factors not used directly in the PD model) that could raise concerns about representativeness.

Given these factors, the Board believes a 10 percent sample for firms with large credit card portfolios is reasonable. Conversely, for firms with relatively small credit card portfolios, relying on a sample risks decreasing the reliability of the loss projections if the characteristics of the sample are not representative of the portfolio as a whole. At the same time, using all reported data for firms with smaller credit card portfolios is not as operationally burdensome, as these portfolios have a smaller impact on run time and memory usage. Given the possible downsides of projecting losses for smaller credit card portfolios using a sample, and the reduced costs of using all reported data, the Board uses all available data to project losses for firms with credit card accounts totaling less than $10 billion in balance.

The resulting sample is filtered to remove irrelevant or problematic data, as follows. First, small business card and corporate card accounts are removed; these accounts are modeled separately in the Other Retail Loan Loss Model. Next, accounts that have been previously closed or charged off, or accounts that have already reached 180 or more days past due, are removed, as these accounts are unlikely to generate further losses.[431] Similar to the bank card estimation data, accounts with missing states are dropped. Also similar to the bank card estimation data, credit scores are adjusted if needed to reflect differences in vendor and version, and origination credit score is used for accounts less than two years old if no refreshed credit score is available. Based on the established range of credit scores, reported credit scores are considered to be invalid when they are greater than 950 except in the cases outlined previously where the credit score range varies substantially from the 300–850 range; in these cases, reported credit scores are considered to be invalid when they are outside of the established range of the

[431] Accounts that are defined by the model as in default that do not meet the above criteria (for instance, bank cards that are five or more cycles past due that have not reached 180 or more days past due) may not have had losses realized by the start of the projection period, so they are not dropped. The treatment of these accounts is discussed further in Section E.ii.d.

score used for those accounts. Similar to estimation data, cycle-ending balance is used where possible, and month-ending balance is used in cases in which cycle-ending balance is missing. In cases in which the balance (cycle-ending balance or month-ending balance) is less than zero, the model treats the account as if the balance were zero. Additionally, in cases in which the credit limit is missing, the model conservatively assumes the credit limit is equal to the current balance (in other words, utilization is 100 percent). Following the stress testing principle of conservatism, and consistent with practices in other stress test models, if after the above adjustments are made, any of the following variables are still missing,[432] the Board will fill in the missing values with conservative values based on the reported data of all firms reporting on FR Y-14M, Schedule D within a given sub-portfolio:

- Credit score: The industry[433] 10th percentile is applied
- Account age: The industry 10th percentile is applied
- Utilization: Calculated based on the unpaid principal balance and credit limit, after the above adjustments. If this is still unavailable after these adjustments, the industry 90th percentile is applied.

Similar to the estimation data, macroeconomic data are merged in using the account state, and the values that are merged reflect quarterly average of the monthly unemployment rates. The unemployment rate projections are drawn from the Stress Test Scenarios.[434] To project values of the state-level unemployment rate, the model assumes that the quarterly change in the unemployment rate is the same in each state as it is in the national scenario. For instance, if the

[432] While firms are responsible for ensuring the completeness and accuracy of data reported in the FR Y-14 information collection, the Board makes efforts to validate firm-reported data and requests resubmissions of data where errors are identified. The treatments described here are applied if data remain deficient after resubmission.
[433] In these calculations, "industry" refers to all observations in the data used to project losses in a given period. The 10th (or 90th) percentile value is calculated based on the distribution of reported data immediately prior to the start of the projection period. For discussion of the use of the 10th percentile loss rate, *see* Section 2.9 of the Stress Testing Policy Statement.
[434] Because the Charge Card PD Model is semi-annual, and 13 quarters of projections are needed to produce estimates of provisions, the model uses the 13th projection quarter of scenario data to produce PD projections in the last semi-annual period.

national unemployment rate is projected to increase by 0.3 percent in a given quarter, the unemployment rate of each state would be projected to increase by 0.3 percent in that quarter as well. This assumption is consistent with treatment of regional macroeconomic variables among other models in the supervisory stress test that use regional macroeconomic variables. For more information and support for the assumptions surrounding regional macroeconomic variables, see Section III.B of the Enhanced Transparency and Public Accountability Proposal.

Also similar to the estimation data cleaning process, the model adjusts the reported account age to account for seasoning that occurs during the projection period. For instance, when projecting the probability of default in the sixth projection quarter for an account that is 18 months old at the start of the projection, the model treats the observation as if it is 36 months old (18 months to start plus 18 months to cover the six quarters that have elapsed).

Finally, accounts are defined as current, delinquent, or defaulted based on the number of cycles the account is past its due date as of the end of the last cycle[435] prior to the start of the projection period. This calculation is used to ensure that treatment is consistent across firms when projecting PD.[436] Based on the number of cycles the account is past due, payment status for each account is defined, as outlined in the introduction to this model description.

(4) Alternatives

Alternative Model Structures

The Credit Card PD Model uses an account-level, multi-period, discrete-time hazard approach, which projects the likelihood that an account will default in each period, given that it

[435] The end of the month is used if end of the cycle is not available or applicable.
[436] In practice, the Board recognizes that there may be ambiguity in the instructions for FR Y-14M, Schedule D.1, Line Item 86 ("Cycles Past Due at Cycle Date"). The Board is soliciting feedback on potential changes to the instructions for that field to reduce ambiguity. See the questions at the end of this Section E.ii.a for additional information.

has not defaulted already. This approach is valuable in the context of the stress test, which requires the projection of credit card loss rates over the course of a hypothetical scenario.

As discussed in the review of literature in Section E.ii.a.(2), the public domain includes numerous examples of hazard models, as well as other types of models, for modeling credit events.[437] The Board considered a wide range of approaches in selecting the appropriate model.

The Board's decided to use an account-level model to maximize the reliability and specificity of the PD projections. Further, relative to other, alternative approaches, the Board found that this approach is most consistent with prevailing economic theory, according to the Board's experience and expertise. The Board also considered using a segment-level transition matrix approach, in which accounts are apportioned into different segments and a share of accounts in each segment is projected to default in each quarter. The segment-level approach has the advantage of requiring less complex input data, reducing the reporting burden on firms. However, the aggregated nature of this alternative model structure limits the model's ability to account for account-specific variation in probability of default, and generally provides less flexibility in structure compared to an account-level approach. Accounting for account-specific variation is important as it ensures the model can accurately project default rates based on characteristics of the portfolio across firms and across time, without over- or under-predicting default rates on accounts with different characteristics. Meanwhile, the flexible structure allows for the inclusion of more factors in the model that can capture a variety of different risks, aligning with the stress testing principle of robustness. Due to these considerations, the Board determined that the account-level model was preferable.

[437] *See*, *e.g.*, Calem and Lacour-Little (2002): and An et al (2010): An, Xudong and Deng, Yongheng and Rosenblatt, Eric and Yao, Vincent, 2010, Model Stability and the Subprime Mortgage Crisis, Journal of Real Estate Finance and Economics.

Additionally, the use of a multi-period model, as opposed to a single-period model, is necessitated by the design of the stress test. The stress test uses quarterly loss estimates to produce projections of the balance sheets of covered institutions over a nine-quarter horizon. This substantially limits the utility of model structures that produce a single estimate of losses, rather than a path. The chosen multi-period hazard approach provides quarterly projections of default rates, allowing for projections of not just the total default rate but its shape.

Additionally, only one outcome variable, default, is considered. As a result, other, competing, outcomes, such as the likelihood that a borrower voluntarily closes an account, do not enter the model. This choice simplifies the modeling framework as it does not require the development of additional specifications to account for closure of a fully paid account, which can be initiated by either the lender or the borrower. Instead, account closures are not considered in the model. Including account closure directly in the model would allow it to account for certain situations or economic environments that would lead to especially high or low closure rates. These could indirectly impact PD, as accounts that close voluntarily by construction cannot default. However, the Board believes that the simplicity of the one-outcome approach outweighs the drawbacks. Due to the supervisory stress test's assumption of a constant balance sheet, the potential impact of events like closure is further mitigated because the model assumes that closed accounts are replaced with newly originated balances. Because the stress test assumes that closed accounts are replaced with new accounts with the same characteristics, the rate of account closure does not meaningfully impact the number of accounts in the portfolio that are able to default.

Given these choices, the Board considered other model structures for projecting a multi-period model, in addition to a hazard model. One alternative to a hazard model is a state transition model (see, for instance, Chen et al. 2020),[438] under which accounts are allowed to transition between states (for instance, current, delinquent, etc.) in each period. This approach allows for the tracking of the path of account behavior over the course of the projection period and allows the account characteristics to update dynamically through the period. State transition models are particularly useful when projecting default in situations in which the factors that predict higher or lower default risk vary over the course of the path of the account to default. However, modeling additional transitions could cause errors to compound in cases where the individual transitions are measured imprecisely, reducing the reliability of the model projections. By comparison, the hazard model is simpler and directly projects the likelihood of default based on starting characteristics; with this simpler structure, a hazard model is less susceptible to this limitation. Because credit cards are generally unsecured[439] and there is no repossession or foreclosure process, credit cards tend to have a relatively direct trajectory toward default. Given the risks arising from projecting each transition separately and imprecisely, and because the advantages of state transition models are less important given the characteristics of credit cards, a hazard model is used rather than a state transition model.

Finally, the Board considered approaches relying on machine learning algorithms to model credit card PD rates.[440] As discussed in the review of literature in Section E.ii.a.(2), machine learning algorithms have gained traction in academic literature due to their potential to improve model accuracy; see, for example, Butaru et al. (2016). Unlike traditional modeling,

[438] Chen, Q., D. Glennon, and A. Golan (2020). Estimating Conditional Mortgage Delinquency Transition Matrices. Office of Comptroller of the Currency Working Paper 2020-05. State transition models are used by many industry and government actors, such as HUD (see Annual Actuarial Review of the FHA Mutual Mortgage Insurance Fund Forward Loans – Fiscal Year 2024. United States Department of Housing and Urban Development. November 13, 2024, https://www.hud.gov/sites/dfiles/Housing/documents/2024-MMI-Forward-Loans-Final-Report.pdf.)
[439] Less than 1 percent of accounts are secured by collateral, based on analysis of FR Y-14M data as of December 2024.
[440] One example of a machine learning algorithm that can be used in this context is a random forest model.

where programmers start with a model structure and selected variables, and produce estimates of the pre-defined relationships between the variables, machine learning algorithms rely on vast computational power to test numerous types of relationships between variables to determine the most important relationships. Machine learning algorithms provide significant flexibility, as the structure of the model is not pre-defined, and algorithms are powerful tools for producing models with high levels of in-sample fit; these tools are especially useful when large amounts of data are available, like for the Credit Card Model. While the Board will continue to research potential applications of machine learning algorithms, a major drawback currently is that machine learning algorithms can be less interpretable than traditional modeling structures. In the context of the supervisory stress test, explainability of the model results is of paramount importance, to understand the underlying factors that lead certain accounts to be classified as more or less risky. Therefore, the Board does not currently employ machine learning algorithms in the supervisory stress test, including in the Credit Card PD Model.

Alternative Covariates

Given the chosen model structure, many possible variables and transformations of variables were considered for inclusion in the model. This section describes alternative specifications of the transition equations and the determinations that led to the rejection of the alternatives. Broadly, as outlined in Section E.ii.a.(2), the variable choices are made to maximize economic support (as described in that section) and statistical fit while ensuring that the model was sufficiently simple, in line with the stress testing policy of simplicity. When these factors do not provide a single best option, the principle of conservatism is used to select the model with the covariates that produce higher loss estimates.

As discussed in Section E.ii.a.(2), variables included across the different equations within a sub-portfolio (bank card or charge card) are generally chosen simultaneously, except in circumstances in which a certain variable is not interpretable in an equation.[441] The Board considered treating each of the nine Bank Card PD equations and each of the four Charge Card PD equations individually and determining appropriate variables on an equation-by-equation basis. This would allow for the inclusion of certain terms that impact default only for particular time horizons or certain starting statuses. However, the Board ultimately determined that it was reasonable to make universal variable choices across sub-portfolios. While this ensures that the factors that are predictive of default risk in the model are generally the same for each of the equations, the exact sensitivity of default to certain variables may differ between equations, as the coefficients for a given term may vary across equations. Additionally, maintaining a constant selection of variables increases the interpretability of the model results, as it ensures the same factors predict default risk, regardless of starting status. Finally, maintaining a constant selection of variables across equations reduces the Board resources needed to construct and maintain the models.

Based on this decision, alternatives to the chosen covariates are considered. The model accounts for a wide range of account and borrower characteristics that impact default; however, some variables considered for inclusion are not incorporated into the final model. A brief discussion of these variables follows.

First, the Board considered accounting for differences in default risk between transactor and revolver accounts, as described below. Bank card account holders can be divided into two broad categories based on their propensity to pay their entire balance each cycle. "Transactors"

[441] As noted in that discussion, the current-to-inactive equations also include slightly fewer terms than the other equations in the model.

are account holders who pay their balance in full each cycle, while "revolvers" are those who carry a balance across cycles. Given that revolvers are not fully paying their debt each month, revolvers may be more likely to default than transactors, other factors held equal. Among revolvers, there is further variation in risk based on payment rates; borrowers who make only the minimum payment are potentially riskier than borrowers who make larger payments. Quantitative evidence that higher payment rates (where transactors are borrowers with 100 percent payment rates) are associated with lower default risk is observed in academic literature; see, for example, Butaru et al. (2016) and Keys and Wang (2019)[442]. While accounting for differences between transactors and revolvers—and differences in payment rates—may be valuable, there are challenges in accounting for these characteristics in the context of the supervisory stress test. Notably, while the behavior of account holders as transactors or revolvers is somewhat persistent, it can change over time; many borrowers pay off their balance in most but not all periods. Similarly, payment rates can change meaningfully over time. As additional support, the Board conducted analysis regarding inclusion of these terms by testing versions of the model including payment rate or whether an account behaved as a transactor or a revolver. This analysis indicated that the upsides of including these terms were limited, given that they may be correlated with other variables in the model, such as credit score. Given the complications of modeling how account holders can adjust payment rates or switch between acting as transactors or revolvers in different economic environments, and the limited expected benefits of accounting for these terms, the Board does not include these factors in the Bank Cards PD Model.

[442] Keys, Benjamin and Jialan Wang, 2019. "Minimum Payments and Debt Paydown in Consumer Credit Cards." Journal of Financial Economics 131(03): 528-548.

Next, the Board considered accounting for the tightness of the lending environment. During periods of credit expansion, lenders may extend credit to borrowers who may not otherwise be eligible during periods of credit tightening. These borrowers may be riskier than other borrowers in ways not identifiable through observable characteristics. A common measure of credit availability is the Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS), which measures whether standards are tightening or loosening for various loan categories (including credit cards), in addition to other features of the lending environment. By incorporating responses from SLOOS into the supervisory stress test model, the Board would potentially be able to account for these unobservable differences in credit quality. While the inclusion of responses from SLOOS may improve model performance, the questions on the survey are qualitative and highly aggregated and consequently the values reported may not be precise or stable. In addition, a drawback of incorporating SLOOS or other qualitative measures of economic tightness is that it is challenging to project the path of indexes like SLOOS in the projection period. Given the complexity required to model qualitative assessments of the lending environment over the scenario, the Board does not include measures of credit availability in the Credit Card PD Model. However, because of the potential importance of credit availability, the Board may consider in the future including measures of tightness in the lending environment in the future.

Among variables that are included in the model, the Board considered alternative transformations and manipulations of these variables. Alternative decisions around transformations are discussed separately for continuous variables (those with a numerical range) and categorical variables (those that are divided into discrete categories).

For continuous variables, such as credit limit (for bank card), utilization (for bank card), account age (for bank card and charge card), and credit score (for bank card and charge card), alternatives are intended to account for the fact that the impact of the variable may be non-linear, meaning it varies at different values of the variable. A simple, flexible implementation to account for non-linear effects would be to separate continuous variables into categories, essentially turning continuous variables into categorical variables (referred to as "binning"). Binning is beneficial in cases in which small movements in a variable do not have large impacts on PD, but rather PD "leaps" at certain trigger points. Academic literature and empirical analysis conducted by the Board indicates that grouping continuous variables into bins produces reasonable outputs that are accurate at an aggregate level, even if they do not account for variation in default risk within the bins. Bins are therefore used in the Charge Card PD model. However, in the Bank Card PD model, the Board avoids using bins; due to the market size of the portfolio and particular concerns that by creating "cliffs" in model projections of PD, binning may result in loss rates that may not accurately reflect corresponding changes in risk at the boundaries of the bins. In particular, as accounts move from one bin to another, changes in loss projections can be large, even if the underlying shift in the account characteristics is small. An alternative modeling choice to binning continuous variables is splining continuous variables, as defined in Section E.ii.a.(2). Splines are beneficial due their continuous nature; unlike bins, with splines there is no "jump" in default risk at any given value of a variable. However, splines can be sensitive to the selection of the "knot"; moving the knot location by a small amount can have meaningful impacts on PD projections. Therefore, when using splines, care must be taken to place knots such that PD projections are reasonable at all levels of the variable. This process of knot selection is resource-intensive; while this process is justified for the Bank Card PD model, given the difficulty of selecting appropriate spline knots, the simpler binning approach was preferred for the Charge Card PD model.[443] A further discussion of the treatment of continuous variables is available in Section E.iii.a.

For categorical variables, specification is simpler; including a categorical variable in the model calibrates the change in likelihood of default for accounts in a given category compared to another. However, the Board determined, based on analysis of the historical data, that categorical variables do not impact PD in a vacuum; rather, they often have higher or lower effects based on the borrower credit score. A full discussion of the interaction terms is available in Section E.ii.a.(2). However, an alternative approach is to simplify the model structure to remove these interaction terms. While the rationale for including these interactions is available in Section E.ii.a.(2), the inclusion of interactions can lead to noisy estimates in certain equations or segments, and removing the interaction terms would simplify the model, reducing the computing power needed to estimate the model parameters and produce model projections. Despite the potential advantages of removing the interaction terms, the model continues to use them to ensure that the model is reflective of changes in risk levels for categorical variables at different points in the credit score distribution. The Board may consider removing certain interactions if future empirical analysis determines them to be reflective of spurious relationships rather than of differences in risk.

In addition to the account and borrower information included in the model, the Credit Card PD Model also uses unemployment rate to incorporate the impact of changes in the macroeconomic environment. The Board uses unemployment rates to proxy for broad economic stress and households' ability to pay bills—based on academic literature on credit risk, industry

[443] The models use linear splines to minimize operational cost. Other spline forms, such as cubic splines, can create smoother impacts but are more complex operationally.

best practices, and independent experience and expertise of the Board. Unemployment rates are broadly used in this context because they provide a comprehensive measure of the economic health of households and businesses. Higher unemployment rates can be an indication of stress on household budget constraints. These situations can lead households to default on their loans. The importance of unemployment rate is observed in academic literature across different retail loan products, including credit cards (see, for example, Agarwal and Liu, 2003; and Belotti and Crook, 2013); but also first lien mortgages (see, for example, Elul, Souleles et al., 2010) and home equity lines of credit (Hale, Krainer, and McCarthy, 2020). Despite the evidence in support of using unemployment rate as a broad measure of economic stress, the Board also considered adding additional macroeconomic variables to the model.

Analysis of additional macroeconomic alternatives has been a particular focus in recent years, as credit card delinquency and charge-off rates have increased substantially despite unemployment rates remaining low.[444] The increase in delinquency and charge-offs suggests that additional drivers of default risk may exist that are not currently captured by the model. One potential explanation for this increase is that defaults may be increasing due to a reduction in borrower's purchasing power. Even though unemployment rates have remained low in recent years, the cumulative impact of increased inflation, along with uneven wage growth, has reduced the inflation-adjusted ("real") income of many borrowers. To account for this, the model could rely on real disposable income growth, which proxies for this effect. Prior to the COVID-19 pandemic period, unemployment rate and real disposable income growth were highly correlated;

[444] Historical data on industry credit card charge-off and delinquency rates are available on the Board's website. Charge-Off and Delinquency Rates on Loans and Leases at Commercial Banks, Federal Reserve Board of Governors. https://www.federalreserve.gov/releases/chargeoff/. Among FR Y-14M reporters, increases in past due balance between 2021 and 2024 can be observed in the Large Bank Credit Card and Mortgage Data published by the Federal Reserve Bank of Philadelphia. *See* "Large Bank Credit Card and Mortgage Data." Federal Reserve Bank of Philadelphia. 8 July 2025, https://www.philadelphiafed.org/surveys-and-data/large-bank-credit-card-and-mortgage-data.

therefore, adding real disposable income growth to a model that already included unemployment rate did not improve model predictions significantly. However, in recent years, as these variables have diverged, there is reason to believe including a measure of real income growth, in addition to unemployment, would improve model performance. In the same vein, interest rates across the U.S. economy have increased in recent years. This potentially impacts bank card default rates, as borrowers who carry a balance on their credit card will see increased payments in times of higher interest rates.[445] It is plausible, therefore, that as interest rates increase, more borrowers would be expected to default, and vice versa.

However, despite the theoretical evidence and preliminary statistical evidence for including measures of real income (such as real disposable income) and interest rates, the Board determined that there is not sufficient evidence at this time to incorporate these variables into the Credit Card PD Model as there is not yet sufficient evidence to support the exact specification of these variables that would best predict probability of default. However, the credit card market continues to evolve, as does the macroeconomic environment, and as additional information becomes available, the Board may consider adding additional measures of the macroeconomic environment to the Credit Card PD Model to account for a wider variety of economic scenarios.

(5) Questions

Question E1: In recent years, credit card defaults have increased despite consistently low unemployment. This suggests that other macroeconomic factors other than unemployment rate may be associated with default risk. Should the Board incorporate measures of real income (to account for differences over time in household budget stress) and interest rates (to account for changes in credit card payment amounts) to improve the range of scenarios over which the

[445] Since charge card balances must be repaid in full each month, interest rates should be less impactful to the Charge Card PD model compared to the Bank Card PD model.

Credit Car PD Model produces accurate projections? For example, shorter-term or longer-term aggregate real income growth could be incorporated into the Credit Card PD Model, potentially accounting for the interaction of this variable with credit limit or credit score to capture different magnitudes of effects across borrowers. As another example, when interest rates (i.e., the prime rate) increase, finance charges increase for revolvers, causing debt burdens to increase and borrowers to draw down their available balance faster. Should the Board incorporate changes in the prime rate, potentially applied only to borrowers who are revolvers, to account for this effect? What are the advantages and disadvantages of including the above variables in the model?

Question E2: The Board believes there is ambiguity in the reporting instructions for FR Y-14M, Schedule D.1, Line Item 86 ("Cycles Past Due at Cycle Date") if firms have different thresholds for defining cycles past due (i.e., a firm could consider a loan to be one cycle past due if a minimum payment has not been made one full billing cycle since the initial due date, whereas another firm could consider a loan to be one cycle past due if a minimum payment has not been made as of the initial due date). What clarifications should be made to the instructions for this field to ensure that it is reported consistently by all firms reporting FR Y-14M, Schedule D.1? If changes to Line Item 86 were made to ensure consistency and clarity, are there other delinquency-related fields that could be removed from FR Y-14M, Schedule D.1 to reduce reporting burden?

Question E3: The FR Y-14M instructions allow reporters to report any commercially available credit score. This provides flexibility to reporters but requires the Board to make assumptions about how the risk of a borrower default compares across different credit score vendors and versions. What adjustments, if any, should the Board make to reported credit score *in the Credit Card PD Model to account for the use of different credit score vendors and versions?*

b. *Loss Given Default Model*

(1) Description

The LGD model projects the share of the EAD that the lender will not be able to recover after the borrower enters default. While the FR Y-14M, Schedule D.1 instructions provide fields for gross charge-off amount and recovery amount[446]—with the field definitions also applicable for the Historic Bank Cards Data—coverage of these variables during the 2008 financial crisis period, the most notable prolonged economic stress event in recent history, is limited to a few firms; even among these firms, these fields are often missing, raising data quality concerns. Given the limited reliable historical data available during this period, the Board relies on other, aggregated data sources to project LGD for defaulted credit cards in the supervisory stress test model.

For the Bank Card LGD Model, due to the limited historical account-level information available, the Board instead relies on historical information collected on FR Y-9C, Schedule HI-B, to estimate the share of the gross charged-off balances recovered in different macroeconomic environments. In particular, among certain credit card issuers reporting historical charge-off information during the relevant sample period, the LGD rate in a quarter was assumed to be the average level of recoveries over the two succeeding quarters divided by the gross charge-off level in that quarter, subtracted from one. Using the average of two quarters smooths historical recovery rates while accounting for uncertainty in the exact timing of the recovery. For the supervisory severely adverse scenario, this LGD rate was calibrated using the average industry

[446] Line items 62 and 63 on that schedule, respectively.

recovery rate over the period starting in the fourth quarter of 2007 and ending in the fourth quarter of 2009, corresponding to the period over which there was substantial strain in the credit card market. Based on this calculation, the LGD is calibrated to be 90 percent. This is slightly higher than the LGD would be using the same methodology applied to later periods, during the economic growth period following the 2008 financial crisis. This is reflective of the fact that recovery rates would be expected to fall during periods of economic stress, as borrowers are less likely to have the ability to even partially repay their defaulted debt in these periods.

For the Charge Card LGD Model, loss severity data is calculated using historical data reported on the FR Y-14Q.[447] The FR Y-14Q data includes information on gross charge-offs[448] (both contractual and bankruptcy charge-offs) as well as net charge-offs (which are inclusive of recoveries). LGD under the supervisory severely adverse scenario was calibrated as the total net charge-offs from the first quarter of 2008 through the first quarter of 2010 divided by the total gross charge-offs over this period. Based on this calculation, the LGD is calibrated to a certain percentage under the supervisory severely adverse scenario.[449] Similar to bank card LGD, this is higher than the LGD would be using the same methodology applied to later periods, during the economic growth period following the 2008 financial crisis.

(2) Support for Model Decisions

While the public domain includes many examples of modeling credit card PD rates, research on credit card LGD is comparatively less robust. Bellotti and Crook (2009)[450] show using data on credit cards in the United Kingdom that macroeconomic factors such as bank

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[447] Prior to the creation of the FR Y-14M report in June 2012, information on credit cards was collected on the FR Y-14Q report. The reliance on FR Y-14Q data is due to the fact that credit card and charge card loss rates are not broken out separately on FR Y-9C, Schedule HI-B.

[448] Gross charge-offs are equivalent to the exposure at default for accounts that were charged-off.

[449] The exact percentage is not disclosed in this document, as it may be confidential supervisory information.

[450] Bellotti, T., and J. Crook (2009). "LGD models for UK Retail Credit Cards," Credit Research Centre Working Paper, University of Edinburgh Business School.

interest rates and the unemployment rate impact LGD, indicating that LGD should be expected to be higher during economic downturns than during benign periods. The LGD model used in the supervisory stress test draws on Banerjee and Canals-Cerdá (2012), which similarly uses aggregated data from FR Y-9C reports to calibrate LGD.

Because virtually all credit cards are unsecured,[451] recovery rates on defaulted credit cards tend to be low. Also, as collateral values, which often provide a more concrete basis for estimating recovery amounts, are not applicable for credit cards, it is challenging to calibrate recovery rates for individual accounts. Generally, the lack of reliable historical data on account-level credit card recoveries, as well as limited external research to support a more complex LGD model, justify a simple approach.

The dates used to calibrate the models are intended to cover a period of economic stress similar to that contemplated by the supervisory severely adverse scenario. The Board tested using wider ranges of dates for calibrating the Bank Card LGD level and determined that 90 percent LGD was robust across different definitions of the stress period. One caveat is that between 2009Q4 and 2010Q1, the balances reported on the FR Y-9C—and thus the charge-offs and the recoveries—increased sharply due to instruction changes that expanded the population of loans required to be reported on the FR Y-9C. These sharp changes could raise concerns about the representativeness of the data reported on the FR Y-9C report. Despite these concerns, the Board assessed calculated credit card recovery rates before and after the instruction changes were implemented and found that they remained stable, despite the sharp increase in balances. Calculated LGD rates in 2010 were less than 0.5 percentage points below their 2009 levels; even

[451] Less than 1 percent of accounts are secured by collateral, based on analysis of FR Y-14M data as of December 2024. Because of the immaterial share of secured credit cards, the Board does not apply a specific treatment for secured credit cards in the supervisory stress test.

this small reduction could be partially due to the economic recovery, in addition to any reporting changes. Given these findings, the Board relies on data from the fourth quarter of 2007 through the fourth quarter of 2009 to calibrate Bank Card LGD.

While historical Charge Card LGD varies more depending on the period used, the calculated recovery rate appears reasonable and is not driven by outliers in the data during that period. The period from the first quarter of 2008 through the first quarter of 2010 is used to align with the peak of the observed LGD during the 2008 financial crisis period, to align with the stress testing principle of conservatism.

Recovery rates have notably increased since 2011 in both the bank card and charge card portfolios, as the economic environment improved. It is possible that changes to bank risk management, supervision, or regulation, in addition to improvements in the economic environment, could also have contributed to improved recovery rates. However, this is difficult to assess using the information available. Therefore, despite the decline in observed LGD in recent years, the Board continues to calibrate the supervisory stress test LGD to the 2008 financial crisis period, in line with the stress testing principles of conservatism and focus on the ability to evaluate the impact of severe economic stress.

While a simple, industry-level approach is used to model LGD, bank cards and charge cards are calibrated separately. This is reflective of fundamental differences between the sub-portfolios and borrower populations. Historical data reported on the FR Y-14Q schedule used to calibrate LGD for charge cards confirms the intuition that there are significant, persistent differences in LGD between bank cards and charge cards.

Finally, LGD is calibrated at an industry, rather than firm, level. This is consistent with the Stress Testing Policy Statement, which notes that “firm-specific fixed effects are generally not incorporated in supervisory models to avoid the assumption that unobserved firm-specific historical patterns will continue in the future."[452] While FR Y-9C data indicates that there are differences in firm-level LGD, these differences are not carried forward to account for the risk that these firm-specific differences may not persist in the future.

(3) Adjustments and Data Cleaning Steps

The Bank Card LGD projection is calibrated using historical data reported on the FR Y-9C. To ensure reliable projections, firms are included in the historical data if they meet each of the below criteria:

- The firm reported gross charge-off and recovery information on FR Y-9C, Schedule HI-B covering the entirety of the 2008 financial crisis period.
- The balances of the portfolio exceeded $2 billion as of 2012. This is a historical decision determined based on when the LGD methodology was created.

The balance threshold is intended to prevent de minimis portfolios from impacting the LGD calculation. Because of the small share of the credit card market made up of firms with de minimis portfolios, excluding these firms does not meaningfully impact the estimated LGD. However, these small portfolios are more susceptible to outlier values and are excluded to avoid these outliers impacting the calibration of LGD. These criteria align the data used to calibrate the LGD parameter closely with the portfolio of credit cards among firms subject to the stress test, while restricting to firms for which data are available during an important period of economic stress. The inclusion of many firms in the calculation ensures that results are not overly driven by any one firm, in line with the stress testing principle of robustness and stability.

To understand how both changes in the credit card market over time and differences between large and small firms may impact LGD, the Board assessed the sensitivity of the LGD

[452] *See* Section 2.4 of the Stress Testing Policy Statement.

calibration to the choice of included firms by recalculating LGD including more firms in the data. When applying other thresholds (for instance, $1.5 billion) or eliminating the threshold entirely, the calculated LGD varies from its value based on the firms included based on the criteria described above by less than 0.5 percentage points.

The Board uses charge card data from major charge card issuers to calibrate the Charge Card LGD projection.

(4) Alternatives

The Board's approach to modeling credit card LGD provides simple, reasonable, and consistent estimates of the share of defaulted balance that is not projected to be recovered. This section describes alternatives to the chosen approach.

As noted previously, one alternative is to adjust the range of historical data over which LGD under the supervisory severely adverse scenario is projected. However, analysis performed by the Board indicates that across reasonable definitions of the 2008 financial crisis period, the calculated LGD rate will remain close to its calibrated value. Given that the calculated LGD would not meaningfully change by adjusting the time period, the Board determined that the selected time period is reasonable.

A more fundamental alternative is to develop a regression model framework for projecting LGD at an account level, based on account, borrower, and macroeconomic characteristics. Account-level data on gross charge-offs and recoveries are reported in the FR Y-14M, providing unique data that could be used for calibrating a more sophisticated model. A more sophisticated model could lead to more accurate projections for certain accounts that have features with higher recovery values, or based on when in the scenario path the account defaults. As the time series of reported data expands, the Board will continue to evaluate the potential model improvements that would result from use of the account-level loss data; at this point, limited historical data, as well as limited staff resources available for producing such a model, lead the Board to choose this simpler approach.

A final alternative considered for the Credit Card LGD Model was to calibrate projections based on historical recovery rates of individual firms. However, as noted in Section E.ii.b.(2), the supervisory stress test models generally do not include features that would explicitly differentiate loss projections by firm; for this reason, an industry-level approach is preferred instead.

c. Exposure at Default Model

(1) Description

As stated earlier, the projected EAD is equal to the sum of the amount outstanding on the account and the estimated amount of the credit line that is likely to be drawn down by the borrower between the beginning of the projection horizon and the time of default (the "loan-over-line equivalency factor," or "LLEQ"). This section first describes the Bank Card EAD model; the simpler Charge Card EAD model is described after.

The amount outstanding on the account directly relies on the principal balance amount of the account. The estimated amount of the credit line that is likely to be drawn down by the borrower is estimated based on the Bank Cards Data, similar to the Bank Card PD Model. Whereas the Bank Card PD Model uses a 0.1 percent sample of the data, the Bank Card EAD Model uses a larger 1 percent sample to ensure a sufficient number of defaulted accounts are included to produce reliable results. The Bank Card LLEQ projections are calibrated based on Bank Cards Data covering the period January 2008 through June 2023.

To calibrate the LLEQ projections, accounts that eventually default are tracked over the two years prior to the default date.[453] This allows the model to project the share of the credit limit that will be drawn between a given time period (the "observation time") and the date of default.

Mathematically, LLEQ can be defined as in Equation E5:

Equation E5 – Definition of LLEQ

$$LLEQ_t = \frac{[UPB_{tD} - UPB_t]}{Line_t}$$

where:

- t is the observation time;
- $LLEQ_t$ is the LLEQ at the observation time;
- UPB_{tD} is the balance at the time of default;
- UPB_t is the balance at the observation time; and
- $Line_t$ is the credit limit on the account at the observation time.

EAD is defined as in Equation E6:

Equation E6 – Definition of EAD Under LLEQ Framework

$$EAD_{tD} = max\ (0\ , UPB_t + \widehat{LLEQ}_t * Line_t)$$

where:

- t is the observation time;
- EAD_{tD} is the EAD;
- $\widehat{LLEQ}_t$ is the projected LLEQ for a given account based on the model at the observation time; and
- $Line_t$ is the credit limit on the account at the observation time.

Projected EAD is also ensured to be positive by replacing negative projections from the linear model, which is a rare occurrence, with 0 dollars.

453 The default date is defined as the quarter in which the account reaches five or more cycles past due.

As described in detail below, the Bank Card EAD is adjusted to exclude delinquent interest and fees, as delinquent interest and fees are often reversed upon default and reflected in reduced pre-provision net revenue rather than as credit losses.

The Bank Card EAD model uses six different LLEQ equations, described as follows. LLEQ is calibrated separately for accounts that are current at the observation time and accounts that are delinquent at the time of observation. For each of current and delinquent accounts, separate equations model different time horizons, as follows:

- The short-term equation reflects LLEQ among accounts defaulting in the six months following the observation date.
- The medium-term equation reflects LLEQ among accounts defaulting between seven and twelve months following the observation date.
- The long-term equation reflects LLEQ among accounts defaulting between 13 and 24 months following the observation date.

Differentiating equations by starting delinquency status accounts for the fact that delinquent accounts likely already have high utilization, may also have their credit lines closed or frozen, and will have challenges making additional draws. As a result, LLEQ is generally low for delinquent accounts, whereas it is often substantially higher for current accounts. The equations for the different time horizons account for the increased time borrowers will have to make additional draws as the time to default is extended.

Within each equation, account and borrower characteristics are included to increase the accuracy of the EAD projections. A range of account and borrower characteristics (assigned based on the observation time)—including the utilization rate, borrower credit score, unpaid principal balance, age of account, product type (co-brand, affinity, etc.), and whether the card is securitized (designated for inclusion in a master trust)—are used in the equations.

Mathematically, LLEQ is estimated using ordinary least squares ("OLS") regression equations. OLS regressions are widely used in statistical analysis due to their simple implementation, interpretability, and accuracy. The coefficient on a given variable in an OLS regression can be interpreted as the change in the outcome (in this case, LLEQ) expected given a one-unit change in the value of the variable.

One consideration is that while the models are calibrated to capture the risk of default over eight quarters, the model is applied to project losses over thirteen quarters to compute provisions as well as loan losses.[454] To produce projections in the ninth through thirteenth projection quarters, the LLEQ is assumed to be the same as the LLEQ projected in the eighth projection quarter. This approach is used to maximize the accuracy of the LLEQ calculation, and accounts for potential unreliability in using data from additional quarters ahead to fit the EAD model parameters. For further discussion of this assumption, *see* Section E.ii.c.(4) and Section E.iii.b. The full specification of the EAD model is available in Table E6 and Table E7.

Table E6 - Bank Card EAD Model: LLEQ Equations from Current

		Current Short-Term		Current Medium-Term		Current Long-Term	
Parameter	Variable Description	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Account Age	Flag at 3 Years	-0.0227	0.0004	-0.0700	0.0005	-0.1177	0.0007
Account Balance		-	-	0.0000	0.0000	0.0000	0.0000
Affinity Card		-0.0008	0.0010	-0.0274	0.0012	-0.0519	0.0015
Credit Limit	Knot at $300	-0.0010	0.0000	-0.0013	0.0000	-0.0019	0.0000
	Knot at $500	0.0007	0.0000	0.0009	0.0000	0.0013	0.0000
	Knot at $1k	0.0002	0.0000	0.0003	0.0000	0.0004	0.0000
	Knot at $2k	0.0001	0.0000	0.0001	0.0000	0.0001	0.0000
	Knot at $5k	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Credit Score	Knot at 580	0.0001	0.0000	0.0005	0.0000	0.0019	0.0000
	Knot at 660	-0.0013	0.0000	-0.0017	0.0000	-0.0031	0.0000
General Purpose Card		-0.0286	0.0004	0.0743	0.0005	0.1627	0.0007
Horizon	Q1	-0.1025	0.0015	-	-	-	-
	Q3	-	-	-0.0365	0.0004	-	-
Intercept		0.7654	0.0008	1.2658	0.0010	1.5554	0.0012
Securitized		0.0345	0.0004	0.0048	0.0005	-0.0539	0.0006
Utilization Rate	Knot at 10%	-0.6538	0.0057	-1.6661	0.0062	-1.3227	0.0067
	Knot at 25%	0.5896	0.0064	1.1361	0.0070	0.5015	0.0076

[454] *See* Section B in the Aggregation Models Documentation (Provisions Model) for more information. Generally, the Board assumes firms will hold allowances sufficient to cover the four succeeding quarters of loan losses in a portfolio and will provision to reach that allowance level (subject to certain caveats described in that section). Therefore, to project allowances in the ninth quarter of the projection horizon, the Board must project losses in the tenth through thirteenth quarters.

Table E7 - Bank Card EAD Model: LLEQ Equations from Delinquent

Parameter	Variable Description	Delinquent Short-Term Estimate	Delinquent Short-Term Std. Error	Delinquent Medium-Term Estimate	Delinquent Medium-Term Std. Error	Delinquent Long-Term Estimate	Delinquent Long-Term Std. Error
Account Age	Flag at 3 Years	0.0044	0.0001	-0.0211	0.0013	-0.0414	0.0024
Account Balance		-	-	0.0000	0.0000	0.0000	0.0000
Affinity Card		0.0047	0.0004	-0.0249	0.0031	-0.0608	0.0041
Credit Limit	Knot at $300	-0.0002	0.0000	-0.0005	0.0000	-0.0008	0.0000
	Knot at $500	0.0001	0.0000	0.0003	0.0000	0.0005	0.0000
	Knot at $1k	0.0001	0.0000	0.0002	0.0000	0.0002	0.0000
	Knot at $2k	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Knot at $5k	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Credit Score	Knot at 580	0.0001	0.0000	-0.0001	0.0000	0.0002	0.0000
	Knot at 660	-0.0005	0.0000	-0.0008	0.0001	-0.0008	0.0001
General Purpose Card		-0.0639	0.0002	-0.0220	0.0014	0.0061	0.0020
Horizon	Q1	0.0096	0.0002	-	-	-	-
	Q3	-	-	0.0059	0.0012	-	-
Intercept		0.1884	0.0005	0.7172	0.0051	0.9455	0.0064
Securitized		0.0322	0.0002	0.0515	0.0014	0.0145	0.0018
Severely Delinquent		-0.0800	0.0001	-0.1012	0.0021	-0.1093	0.0032
Utilization Rate	Knot at 10%	0.0852	0.0031	-1.8144	0.0330	-2.1433	0.0409
	Knot at 25%	-0.0222	0.0034	1.5433	0.0347	1.6358	0.0436

where:

- Account balance refers to the balance on the account. It is restricted to be no less than $0 and no greater than $12,000 (balances greater than $12,000 are assumed to be $12,000). The cap on the balance variable is aligned with the highest credit limit value used in the model, as described below.
- Account age is the age of the account, defined as the calendar year of default minus the calendar year of origination. The coefficient on the “flag at 3 years” term accounts for the change in expected LLEQ for accounts that are 3 or more years old, compared to accounts less than 3 years old.
- Affinity Card is set to 1 if an account is an affinity card (as described in Section E.ii.a) and set to 0 otherwise.
- General Purpose Card is set to 1 if the account is a general purpose card (as defined in Section E.ii.a) and set to 0 otherwise.
- Securitized is set to 1 if the account has been designated for inclusion in a master trust and is set to 0 otherwise.
- Credit limit refers to the total credit line amount available on an account. The marginal effect of credit limit on LLEQ is zero for credit limits below $300 or above $12,000. Spline knots in between capture the varying impacts at different credit limit levels.
- Credit score refers to the reported credit score of the borrower in a given period. Spline knots account for the varying impacts at different credit scores; the marginal effect of changes to credit score is zero below 580 or above 720.
- Horizon refers to the number of quarters between the start of the projection and the date the default occurs.
- Severely delinquent is set to 1 for accounts that are 90–119 days past due and set to 0 otherwise. It is only applied in the delinquent EAD equations.
- Intercept refers to the intercept of the regression equation.

Unlike bank cards, charge cards generally do not have a preset spending limit. Because of the lack of a credit limit, LLEQ cannot be computed, as the credit limit amount is the denominator of the LLEQ calculation. Instead, EAD is calculated as a fixed percentage of the balance at the start of the projection period (referred to as a "Credit Conversion Factor," or "CCF," approach). Mathematically, CCF is defined in Equation E7:

Equation E7 – Definition of CCF

$$CCF = \frac{UPB_{tD}}{UPB_t}$$

where:

- UPB_{tD} is the balance at the time of default; and
- UPB_t is the balance at the observation time.

Based on CCF, EAD is calculated as in Equation E8:

Equation E8 – Definition of EAD Under LLEQ Framework

$$EAD_{tD} = \widehat{CCF} * [UPB_t]$$

where:

- $\widehat{CCF}$ is the projected CCF for a given account; and
- UPB_t is again the balance at the observation time.

This share is calibrated based on historical data on charge card defaults from the Charge Card Data covering the period 2007-2010 and confirmed using FR Y-14M data covering the period 2013–2018.[455] The analysis compares the balance at a given point prior to default to the

[455] While the Historic Bank Cards Data during the 2008 financial crisis period does not include charge cards, charge card data are available in the FR Y-14M portion of the data. To ensure that the model was not producing unreasonable estimates of EAD because of the exclusion of the 2008 financial crisis period, the same methodology was applied to bank cards, both during the period 2007-2010 and 2013-2018. The analysis shows that EAD was similar during the two periods. Additional analysis applying the methodology to data through 2023 on the FR Y-14M indicates that the EAD for charge cards is calibrated reasonably.

balance at the time of default. For current accounts, the results of this analysis showed that charge card balances at default for current accounts that eventually default is approximately 130 percent of the balance at the time of observation. Therefore, the Charge Card EAD Model projects EAD for accounts that are current at the start of the projection period as 130 percent of the balance at the start of the projection period. For accounts that are delinquent at the time of observation, balance increases are smaller, suggesting balances are similar at the time of default as they are at the time of delinquency. While on average, balances of delinquent accounts do not significantly increase upon default, increases in aggregate balances have been observed in some historical quarters. Given this finding and uncertainty around the true level of expected draws prior to default, the Board sets the EAD for delinquent accounts to 110 percent of the balance at the start of the projection period, in line with the stress testing principle of conservatism. Using 110 percent of the starting balance is appropriately conservative in all historical periods while remaining within the overall range of historical values. Finally, for accounts that have reached default (90 or more days past due) at the start of the projection period, no further draws are assumed; in other words, for these accounts, EAD is assumed to be equal to the balance at the start of the projection period. This assumption is based on the Board's experience and expertise, which suggests that accounts reaching this stage of delinquency have already been frozen or closed and are unlikely to be able to make additional draws.

As referenced earlier, the projected Bank Card EAD is adjusted to exclude delinquent interest and fees. Based on a Board supervisory survey of firm practices, the Board assessed that delinquent interest and fees are often reversed around default and reflected in reduced PPNR rather than as credit losses. To calibrate the portion of projected EAD that is comprised of delinquent interest and fees, the Board uses historical data from 2013 to 2017[456] reported on FR Y-14M, Schedule D.1 (Credit Cards). Data from this period, rather than data from earlier periods, are used for two reasons. First, the passage of the CARD Act in 2009 limited the fees credit card lenders could charge, reducing delinquent interest and fees as a share of delinquent balance in subsequent years. Second, the Historic Bank Cards Data prior to 2013 does not include all firms that report on the FR Y-14M; in particular, firms that did not report the Historic Bank Cards Data have meaningfully different reported interest and fees as a share of delinquent balance compared to firms that reported the Historic Bank Cards Data. Given these findings, the Board determined that using data from 2013 to 2017 was more appropriate than data from earlier periods. Given that the share of delinquent interest and fees declined from the 2008 financial crisis period to the period used for calibrating this adjustment, using data from 2013 through 2017 also increases EAD projections, which is aligned with the stress testing principle of conservatism. In particular, the share of delinquent interest and fees is calculated as the total interest and fees reported from the month the account is last current through the month it reaches 120 days past due, as a share of the total balance on the account when it reaches 120 days past due.[457] While this share varies substantially across firms, at an industry level the Board estimates—using the above methodology—that 6 percent of balance at default is comprised of delinquent interest and fees. As a robustness check, an alternative calculation is used in which delinquent interest and fees are calculated as the difference between the balance when the account reaches 120 days past due and the balance when the account was last current, net of any

[456] While the initial calibration relied on data from 2013 to 2017, the Board reviewed data covering 2019–2022 and confirmed that the share of delinquent interest and fees has not changed substantially compared to the 2013–2017 data.

[457] For this analysis, a threshold based on the number of days an account was past due was used, rather than the cycle-based definition used in modeling. In practice, these definitions align closely.

purchases or payments made during this period. This alternative calculation also estimates that 6 percent of the balance at 120 days past due is comprised of delinquent interest and fees. Therefore, projected EAD is reduced by 6 percent to avoid inappropriately double counting losses from delinquent interest and fees, which are already incorporated into projections of pre-provision net revenue in the supervisory stress test. Board analysis determined that it was not necessary to remove delinquent interest and fees from Charge Card EAD to avoid double counting.

(2) Support for Model Decisions

This section provides additional support for the Credit Card EAD Model. Similar to the discussion of the Credit Card PD Model, this section begins with a review of the relevant literature. Next, the overall model structure, including the use of LLEQ as a method of calibrating additional draws, is supported. Finally, support is provided for the individual variables used in the LLEQ equations.

Review of Literature

Academic literature, as well as independent analysis using the Board's experience and expertise, informs the development of the Credit Card EAD Model. While the literature on EAD is less robust than that on PD, it is valuable nonetheless to ensure that the modeling assumptions used in the Credit Card EAD Model are reasonable. Due to limited academic work on the subject, the Board draws on literature on EAD from other products, in addition to credit cards, to inform modeling. Broadly, analysis shows that account and borrower characteristics are important determinants of EAD, while evidence on macroeconomic factors is more mixed.

Agarwal, Ambrose, and Liu (2006)[458] studied the utilization of home equity lines at and after origination and found that borrowers with a higher expectation of future deterioration in credit quality originate credit lines to preserve financial flexibility. They also find a statistical relationship between a drop in risk score and an increase in credit line utilization. Similarly, Jimenez, Lopez, and Saurina (2009), using a sample of corporate credit lines in Spain, find that firms that default on their credit lines have significantly higher utilization rates; these rates increase as default approaches.

Qi (2009)[459] studied EAD for a sample of current and delinquent accounts over the period of 1998–2008 using loan equivalent factor (LEQ)[460] as the analysis variable and found that borrower and account risk attributes—like account utilization rate, account age, account balance, credit score, and credit limit—are significant drivers of LEQ. Additionally, LEQ was found to be higher in periods when overall default rates were high, which suggests EAD increases in periods when economic conditions worsen. Interestingly, this relationship of EAD and underlying macroeconomic factors was observed during the 2001 recession but not during the 2008 financial crisis period, which could be the result of a reduction in credit card limits by banks at that time. Banerjee and Canals-Cerdá (2012) and Canals-Cerdá and Kerr (2014)[461] similarly find that EAD did not notably increase during the 2008 financial crisis period. This finding that EAD is associated more with account and borrower characteristics than macroeconomic characteristics informs the development of the Credit Card EAD Model design.

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[458] Agarwal, Sumit, Brent Ambrose, and Chunlin Liu. 2006. "Credit Lines and Credit Utilization," Journal of Money, Credit and Banking. Vol.38, issue 1, p. 1-22.
[459] Qi, M. 2009. "Exposure at Default of Unsecured Credit Cards," W.P. Office of the Comptroller of the Currency.
[460] Described in detail in Section E.ii.c.(4).
[461] Canals-Cerdá, Jose J. and Sougata Kerr. 2014, "Forecasting Credit Card Portfolio Losses in the Great Recessions: A Study in Model Risk," Working Paper 14-10 Federal Reserve Bank of Philadelphia.

Support for Model Design

The Credit Card EAD Model projects balance at default as the sum of the balance at the start of the projection period and any additional amount expected to be drawn prior to default. For bank cards, the additional amount expected to be drawn prior to default is projected using an LLEQ approach; for charge cards, this additional amount is projected as a fixed portion of the starting balance, based on delinquency status at the start of the projection period. This section first describes support for the Bank Card EAD Model; the Charge Card EAD Model is discussed afterward.

Bank Card

The Board considered a range of modeling approaches for determining the exposure at default for bank card accounts that reach default. A complete discussion of these potential approaches is available in Section E.ii.c.(4). Compared with these alternatives, LLEQ has several advantages. As discussed in Canals-Cerdá and Kerr (2014) and further in Section E.ii.c.(4), the structure of the LLEQ calculation makes it less susceptible to extreme values than other alternatives, as the generally stable credit limit is used in the denominator. This lack of susceptibility to extreme values produces more reasonable and stable projections for loans with small starting balances or available credit. Therefore, the Board's use of LLEQ is aligned with the stress testing principle of robustness and stability. Additionally, the LLEQ model provides reasonable results with a simple model structure, in line with the stress testing principle of simplicity. Because the credit limit and current balance are directly incorporated into the calculation of LLEQ, the model accounts for these important terms implicitly prior to the inclusion of any other variables in the model. Based on these factors, LLEQ is a reasonable approach to modeling Bank Card EAD.

Given the LLEQ approach, the structure of the equations that are used to estimate LLEQ are discussed. As previously stated, LLEQ is estimated using a series of six equations; separately for current and delinquent accounts, the equations project LLEQ over the short term (the first two projection quarters); the medium term (the third and fourth projection quarters); and the long term (the fifth and following projection quarters). These six equations are estimated separately due to the fundamental differences between the positions of borrowers in these circumstances. Current borrowers generally have access to their lines at the time of observation, giving them increased ability to make large draws prior to their eventual default. On the other hand, delinquent borrowers frequently have already had their line frozen or closed and therefore will have lower LLEQs. Similarly, the equations for different horizons account for differences that result as the horizon expands from short-term to medium-term to long-term. In particular, current borrowers will have increased time to make additional draws—increasing expected LLEQ—while for delinquent borrowers, the firm will have more time to manage the line and, in some cases, achieve reperformance prior to the line defaulting again. Therefore, LLEQ increases over time for current accounts and decreases over time for delinquent accounts. Estimating these six separate equations maximizes the sensitivity of the model to these distinctions.

While the long-term LLEQ equations are used to project EAD in the fifth and following projection quarters, the data used to calibrate the model parameters only relies on data in the two years (or eight quarters) prior to default. As a result, the EAD projections in the ninth through thirteenth projection quarters are based on historical data on draws in the fifth through eighth quarters prior to default. This is due to an observed drop-off in the quality and reliability of data over a horizon longer than two years, which creates challenges in projecting EAD over a long horizon, leading to counterintuitive and unstable results. For current accounts, realized LLEQ is relatively stable over the fifth through eighth quarters; as a result, it is reasonable to extrapolate these values out to additional quarters. For delinquent accounts, there is less stability in realized LLEQ over the fifth through eighth projection quarters, though this is expected given the small number of delinquent accounts that both (1) have not defaulted within two years of the observation and (2) will default after that. Based on these factors, the Board assessed that the long-term equations produce reasonable projections of EAD when applied to the fifth and following projection quarters. See Section E.iii.b of this for further discussion of the use of the EAD Model to project EAD over thirteen quarters.

Charge Card

Unlike bank cards, charge cards generally do not have preset credit limits. Since many of the plausible EAD frameworks (discussed in Section E.ii.c.(4)) rely on credit limit as a way to account for the total potential additional draws, the range of appropriate EAD frameworks is limited for accounts without preset credit limits. Given this characteristic of charge cards, the credit conversion factor approach, which projects EAD as a share of the exposed balance at the start of the projection period, is the most reasonable framework to project EAD for charge cards.

Additionally, charge cards make up a small portion of overall credit card balances. The simple factors applied to current (130 percent) and delinquent (110 percent) accounts appear reasonable across different time periods, as discussed in Section E.ii.c.(1); furthermore, the simple, broad approach avoids the challenges described previously in calibrating CCF for accounts with balances close to zero. Based on the strong and stable historical fit, the Board selected a simple approach based on CCF to project EAD for charge cards.

Support for Variables and Transformations Included in the Model

With the model structure defined, this section next describes support for the individual covariates included in the model. Note that this section is only applicable for bank cards; charge card EAD applies a single factor to the unpaid principal balance at the beginning of the projection period for all accounts.

The factors supporting the inclusion of variables in the Credit Card EAD Model align with the considerations in the Credit Card PD Model. For a review of these considerations, see Section E.ii.a.(2). Similar to the Credit Card PD Model, variables that increase economic support, statistical fit, simplicity, implementation feasibility, and conservatism are included. Like the Credit Card PD Model, the Credit Card EAD Model prioritizes constant variable definitions and inclusion across LLEQ equations. Finally, the Credit Card EAD Model relies on splines to account for the fact that the impact of certain variables may be different at different points in their distribution.

The rest of this section discusses how the above principles are applied to define the variables used in the model. A further discussion of alternative variables, including macroeconomic variables, not included in the model is available in Section E.ii.c.(4).

- Account balance: Account balance can be defined as the utilization rate multiplied by the credit limit amount. Credit limit and utilization are both meaningful determinants of LLEQ; moreover, the interaction between them is also meaningful. Account balance, in effect, serves as an interaction between these two terms, capturing that LLEQ is more sensitive to utilization among higher credit limit accounts. The Board tested the inclusion of account balance in the short-term equations and determined—based on a review of the coefficients and model performance across accounts with different utilization rates and credit limits—that the inclusion of balance did not meaningfully improve performance for the short-term equations. While generally, variables are consistent across the time horizons, in this case, the Board determined based on this analysis that it is reasonable to include account balance only in the medium- and long-term LLEQ equations.
- Account age: LLEQ is lower among seasoned accounts compared to new accounts, potentially reflecting increased information asymmetries for newer accounts, for which lenders know less about the borrowers. Board analysis of historical trends in Bank Cards

Data determined that this effect was concentrated for accounts between two and three years old; therefore, the model is specified such that LLEQ declines between two and three years but does not change outside of that window.

- Affinity card: The coefficients on the medium- and long-term equations show that affinity card accounts have lower LLEQ than other product types; this term is included to capture this effect observed in the historical Bank Cards Data.
- General purpose card: Borrower behavior may vary for cards that can be used broadly, compared to cards that can only be used at a single retailer's stores. While the coefficients vary across equations, in the current medium- and long-term equations—where the coefficients are highest in magnitude—the coefficients are positive, potentially reflecting that borrowers have more ability to use general purpose cards to cover general liquidity needs than private label cards, which can only be used to cover certain purchases.
- Securitized flag: Accounts held in a master trust may behave differently than other cards due to differences in account management for these accounts.
- Credit limit: As observed by the coefficients on credit limit in Table E6 and Table E7, the Bank Cards Data show that historically, accounts with higher credit limits generally have lower LLEQ compared to otherwise similar accounts with lower credit limits. This reflects the fact that a larger balance amount must be drawn to get the same LLEQ for higher credit limit accounts; at the same time, lenders may be more conservative about managing higher credit limit accounts, given the larger stakes. Spline knots capture the varying impacts at different credit limit levels; the impacts generally level out as credit limit increases.
- Credit score: As demonstrated by the coefficients on credit score in Table E6 and Table E7, LLEQ increases with credit score up until approximately 660, then declines after. The observed relationship between credit score and LLEQ is weaker than the relationship between credit score and PD. Given the weaker relationship in LLEQ and the larger number of low credit scores in the defaulted sample compared to the PD sample, a smaller number of knots is needed compared to PD.
- Horizon: Among current accounts, as demonstrated by the coefficients on the horizon variables in Table E6 and Table E7, LLEQ increases as the horizon widens and there is additional time for borrowers to draw down balances. Conversely, among delinquent accounts, LLEQ declines as the horizon widens, as additional time provides opportunities for borrowers to temporarily cure and/or partially repay their balances prior to any eventual default. Based on analysis of Bank Cards Data, in the long term, the effects of horizon level out; therefore, there is no horizon variable included in the long-term equations.
- Severely delinquent: Severely delinquent accounts are unlikely to have access to their credit lines, as lenders will generally freeze the line before it reaches 90 days past due. Without access to the line, LLEQ is lower, as observed by the negative coefficients on the severely delinquent variable in Table E7. This term does not apply to current accounts, which by construction cannot be 90 or more days delinquent.
- Intercept is a statistical term for a variable accounting for the baseline level of risk, before other variables are considered. Intercepts are standard in many regression models.

(3) Adjustments and Data Cleaning Steps

Similar to the Credit Card PD Model, the Board makes several adjustments to ensure the estimation of the Credit Card EAD Model is based on representative data and is minimally impacted by errors or outliers. These adjustments are described in detail in this section. These steps are specific to the Bank Card EAD Model; due to the simple approach used to project Charge Card EAD, no specific data cleaning steps are applied.

Estimation Sampling and Loan Inclusion

As previously described, the Bank Card EAD Model uses a 1 percent sample of accounts in the Bank Cards Data that eventually defaulted, meaning that they reached five or more cycles past due, for accounts that defaulted between February 2008 and June 2023.[462] Accounts are tracked over the two years prior to default. Only bank cards are included; charge cards, small business cards, and corporate credit cards are removed from the sample prior to estimation.

Accounts are excluded if they are missing key variables needed for modeling, or if these values are invalid. Additionally, outliers are in some cases removed. In general, the Board avoids removing data to the extent possible; however, a small number of outliers can, in certain cases, notably impact the model specification. In these cases, removal of outliers is appropriate to avoid these impacts. These conditions are as follows:

- Accounts with balance or utilization less than zero. While in some circumstances credit card balances can be negative, these situations are rare and their inclusion complicates the model framework.
- Accounts with utilization above 300 percent. These situations are rare, affecting less than 1 percent of observations, and are outliers; their inclusion would risk improperly calibrating the model. Based on the Board's judgment and expertise, a threshold of 300 percent appropriately limits the impact of outliers on the model estimation without removing valid data.
- Accounts with a credit limit of less than $10. In general, the Board uses all available data to avoid removing valid data. However, based on the Board's experience and expertise, it

[462] The period of the data starts in January 2008. To ensure there is an observation before default in the data, the earliest an account is allowed to default is February 2008.

is unlikely that any accounts truly have a credit limit below $10; credit limits this low are instead indicative of a data error. This filter only affects less than 0.001 percent of defaulted accounts in the data used to estimate the Credit Card EAD Model.

- Accounts from outside the 50 United States and Washington, DC. Accounts from outside of these geographies represent a small share of total balance and are not generally considered to be domestic credit card accounts, as noted previously in Section E.ii.a.(3). Given these factors, the model applies this filter.
- Accounts with credit scores less than 325 or greater than 900, following any adjustments to the reported credit score described in Section E.ii.a.(3). These are rare and indicative of outliers.
- Accounts with balance at default that is missing, unknown, or zero. For accounts with missing or unknown balance at default, LLEQ cannot be calculated. Zero balance at default is rare and suggestive of a data error, like the firm reducing the balances to zero upon charge-off.
- Accounts that are current and then default within two months. This is unreasonable, as defaulted accounts are defined as those that are five or more cycles past due.
- Similar to the Credit Card PD Model, a handful of firms that historically reported the Bank Cards Data, but dropped off the panel later, were removed, as the Board determined that the inclusion of these firms could threaten the representativeness of the model. In particular, firms are included in the panel if a full, consecutive year of data was reported by that firm at any point starting in or after June 2013. Additionally, in one individual case, a firm was removed from the Historic Bank Cards Data prior to 2013 due to the fact that only a subset of that firm's data was collected by the agency. The Board had concerns about the representativeness of the data given that not all accounts were reported; therefore, observations from this firm are removed from the Historic Bank Cards Data portion of the sample.

Estimation Data Cleaning and Preparation

Following the application of the filters described above, the data is prepared for estimation. The estimation data cleaning process aligns with the process for the PD estimation data, described in Section E.ii.a.(3). No further data cleaning specific to the Credit Card EAD Model is required.

Projection Data Cleaning and Preparation

The projection data in the Credit Card EAD Model rely on the same input data as that of the Credit Card PD Model, as described in Section E.ii.a.(3). No further data cleaning specific to the Credit Card EAD Model is required.

(4) Alternatives

Alternative Model Structures

The Board considered alternative specifications of the Credit Card EAD Model in addition to the model outlined this section. This section describes these alternatives. First, this section discusses alternatives common to both the Bank Card and Charge Card Models; considerations impacting each model are described after. Finally, the section concludes with a discussion of certain considerations related to the current expected credit loss (CECL) accounting standard, which impacts the accounting treatment of credit cards.

There are several plausible approaches for predicting EAD. The range of approaches considered by the Board are outlined below:

- Loan-over-line equivalent factor (LLEQ): This is the methodology used in the Bank Card EAD Model. As defined in Section E.ii.a.(1), LLEQ stands for “loan-over-line equivalent factor”; this is the share of the credit limit amount that will be drawn prior to default. For instance, if the credit limit of an account is $100, the current balance is $50, and $25 is drawn prior to default, the LLEQ will be 25 percent ($25 divided by $100).
- Loan equivalent factor (LEQ): Exposure at default is calculated as the sum of the unpaid principal balance at the time the account is observed plus the share of the *undrawn portion* of the line that will be drawn prior to default. For instance, in the above example, the LEQ will be 50 percent ($25 divided by the difference between the credit limit and the current balance, or $50).
- Credit conversion factor (CCF): This is the methodology used in the Charge Card EAD Model. Exposure at default is calculated as a percentage of the unpaid principal balance at the time the account is observed.
- Exposure at default factor (EADF): Exposure at default is directly calculated as a share of the total credit limit. In other words, EADF directly projects the share of the available credit line that will be drawn by the time of default.

Each of these approaches has advantages and disadvantages in certain contexts. LEQ uses the credit limit to assess the percentage of the undrawn portion of the credit line that will be drawn prior to default. This is in some ways the most intuitive calculation, as it is structured such that an LEQ of 0 percent means no additional draws, while an LEQ of 100 percent means that the line will be entirely drawn down. However, LEQ is very sensitive to extreme values, particularly among accounts that are already fully drawn. For these lines, the undrawn portion of the line is very small, so small changes in observed EAD can lead to large swings in model parameters, a substantial drawback for EAD modeling.

CCF is a simple approach that is useful in certain contexts, such as the Charge Card EAD Model, where credit limit is not defined. However, the lack of inclusion of the credit limit amount can lead to odd results where EAD is projected to be much higher than the credit limit amount if the model is not specified correctly. Additionally, CCF is not defined in cases in which the unpaid principal balance at the time of observation is zero and is extremely volatile when unpaid principal balance at the time of observation is small. For these reasons, CCF is not used for the Bank Card EAD Model.

The EADF approach is less susceptible to extreme values than LEQ or CCF because it projects the share of the credit line drawn at default. Mathematically, volatility arises in LEQ and CCF as the denominator values (in the case of LEQ, the undrawn share of the credit limit and in the case of CCF, the observed balance) approaches zero. Unlike these approaches, the EADF approach uses credit limit in the denominator, which is more stable. However, one drawback of the EADF approach is that for it to produce reasonable outcomes (notably, that EAD is not less than zero), mathematical transformations must be performed to define the regression. By contrast, LLEQ can be reasonably estimated using OLS, which is simple to implement and minimizes the risk of compounding errors as the variable is transformed back and forth.

Compared with these other approaches, LLEQ has several advantages. Unlike LEQ and CCF, as discussed in Canals-Cerdá and Kerr (2014), it is not susceptible to extreme values, as the generally stable credit limit is used in the denominator—in line with the stress testing principle of robustness and stability. Unlike EADF, it provides reasonable results with a simple model structure, in line with the stress testing principle of simplicity. Because the credit limit and current balance are directly incorporated into the outcome variable, the model accounts for these important terms implicitly prior to the inclusion of any other variables in the model. Based on these factors, the Board has found that LLEQ is a reasonable and appropriate approach to modeling Bank Card EAD.

Bank Card

As noted above, many model structures, including LEQ, CCF, EADF, and LLEQ were considered for modeling Bank Card EAD. Ultimately, the LLEQ model was chosen due to its simple implementation and stable, reliable results.

In addition to the overall modeling approach, alternatives to the time period over which the EAD model is calibrated were considered. While the EAD model is used to project exposure at default over the 13 quarters needed to produce supervisory stress test estimates of losses and allowances, the model only considers draws over the two years prior to the date of default. The Board considered widening this window to include draws in more periods prior to default, to ensure that the time period used to estimate the model parameters aligned with the period over which EAD is projected in the supervisory stress test. Despite this alternative's advantages in representativeness, the Board determined to maintain the current two-year (eight-quarter) window. The Board found results to be unreliable when expanding the model past two years before default, due to the complications associated with projecting the path of draws over long horizons. Moreover, the long-term EAD equations produce reasonable results even using the two-year window. This is because average LLEQs are generally stable across quarters in the long-term equation for current accounts, reflecting that the impact of the longer horizon on a borrower's ability to make additional draws plateaus after a handful of quarters. For delinquent accounts, LLEQs are less stable; however, this is likely due to the small number of delinquent accounts that remain in the data for more than two years prior to defaulting. Given the limited data available, the long-term equation provides reasonable estimates of LLEQ for delinquent as well as current accounts. Further analysis of the reliance on the two-year period prior to default in the Bank Card EAD Model is available in Section E.iii.b.

Charge Card

As previously noted, because charge cards generally do not have preset spending limits, the range of alternative specifications is more limited than that for bank cards. Alternative EAD frameworks, such as LLEQ, were considered, but ultimately were not applicable to charge cards due to the lack of a credit limit variable.

Given the CCF framework, which has the benefit of not requiring a credit limit, an alternative approach would be to vary the projected CCF based on observable factors in the data. For instance, adding variables such as unpaid principal balance, borrower credit score, or macroeconomic factors—such as the unemployment rate—could lead to more precise projections of EAD for charge cards. However, the charge card portfolio is substantially smaller than the bank card portfolio; given the smaller portfolio size, charge card projections are less impactful on the supervisory stress test results compared to the bank card projections. The smaller and less impactful portfolio justifies a less complex approach, to align with the stress testing principle of simplicity. At the same time, the Charge Card EAD projections are well calibrated to historical data and produce reasonable projections, even if the projections are not based on a more granular model. Given the solid performance and small size of the portfolio, the Board determined a simpler approach was justified, reducing the complexity of the implementation.

Considerations Related to Current Expected Credit Loss Framework

One alternative that was considered for the Credit Card EAD model was alignment with the current expected credit loss (CECL) framework. Under CECL, institutions are not required to include in their allowance for credit losses projected losses on undrawn portions of unconditionally cancellable credit exposures.[463] Since cardholder agreements frequently state that available credit may be unconditionally cancelled at any time, CECL does not require firms to provision an allowance for credit losses on account of potential future draws. Given CECL instructions, the Board considered an alternative EAD assumption in which losses were only considered on the portion of the line that is drawn at the beginning of the projection period, ignoring any future draws prior to default. However, the Board ultimately determined not to align with this CECL assumption because the supervisory stress test models do not incorporate CECL into the calculation of allowances, as noted in Section III.A in the Enhanced Transparency and Public Accountability Proposal.

Alternative Variables

This section discusses alternative variables considered for inclusion in the Bank Card EAD Model. Given that the Charge Card EAD model relies on a simple calculation based on the starting balance, applied to all accounts, this section focuses on the Bank Card EAD Model only.

As discussed in Section E.ii.c.(2), variables included across the different equations are generally consistent, except in circumstances in which a certain variable is not interpretable in an

[463] *See* question 9, here: "Frequently Asked Questions on the New Accounting Standard on Financial Instruments – Credit Losses," Board of Governors of the Federal Reserve System. 31 July 2020, https://www.federalreserve.gov/supervisionreg/topics/faq-new-accounting-standards-on-financial-instruments-credit-losses.htm.

equation. The Board considered treating each of the six LLEQ equations individually and determining appropriate variables on an equation-by-equation basis. This would allow for the inclusion of certain terms that impact LLEQ only at particular time horizons or only for certain starting statuses. However, the Board ultimately determined that it was reasonable in most cases to make consistent variable choices. While this ensures that the factors that are predictive of default risk in the model are generally the same for each of the equations, the exact sensitivities to certain variables may differ across equations, as the coefficients on each term may vary across equations. Additionally, maintaining a constant selection of variables increases the interpretability of the model results, as it ensures the same factors predict LLEQ, regardless of starting status. Finally, maintaining a constant selection of variables across equations reduces the Board staff resources needed to construct and maintain the models.

While the Bank Card EAD Model accounts for an array of account and borrower characteristics, it notably does not include any variables that proxy for the macroeconomic environment. The Board considered incorporating macroeconomic variables such as unemployment rate, into the model. Qi (2009) indeed finds that EAD generally increases when economic conditions worsen; however, during the 2008 financial crisis period, this historic relationship reversed, potentially due to risk management by firms that reduced the credit lines of at-risk borrowers. Other published research[464] indicates that the inclusion of unemployment rate or other proxies for the macroeconomic environment have minimal effects on projected EAD. Furthermore, the Board tested including unemployment rate and other proxies for the macroeconomic environment in the LLEQ equations and determined the inclusion of these

[464] *See* the review of literature in Section E.ii.c.(2).

variables would not notably impact EAD projections. Given this finding, the Board does not include macroeconomic variables in any of the LLEQ equations.[465]

Finally, similar to the Credit Card PD Model, the LLEQ equations use splines to account for varying impacts of continuous variables at different points in their distributions. This issue is discussed further in Section E.iii.a. As with the Credit Card PD Model, the Board also considered "binning" variables in the LLEQ equations to group continuous variables into broad categories. Similarly, given how different LLEQ behavior is at various account credit limits, the Board considered applying separate LLEQ equations depending on the credit limit of an account.[466] Separate equations and binning allow for improved sensitivity of the model and more flexible projections; however, they have the potential to create distortions (or "cliffs") at the cut-off points. For instance, if accounts with credit limits below x are projected based on one equation, and accounts with credit limits above x are projected based on a different equation, there is the potential that an account with credit limit x-1 would be assigned a substantially different EAD than an account with credit limit x+1. By contrast, splines are beneficial due their continuous nature; unlike with separate equations or bins, with splines there is no "jump" in LLEQ projections at any given value of a variable. However, splines are sensitive to the selection of the "knot"; moving the knot location by a small amount can have meaningful impacts on LLEQ projections. Therefore, when using splines, care must be taken to place knots such that LLEQ projections are reasonable at all levels of the variable. This process of knot

[465] Similarly, analysis of the charge card portfolio demonstrates that the EAD assumption is reasonable across time periods and different macroeconomic environments.
[466] The supervisory stress test model previously included different equations based on the size of the credit line for current accounts. *See* 2025 Stress Test Methodology, p. 43: "For accounts that are current, the Board estimates separate models for segments with credit lines of different sizes."

selection is resource-intensive but was selected given concerns about the distortions to the credit card market that could arise due to the cliffs from binning or separately estimated equations.

(5) Questions

Question E4: What are the advantages and disadvantages of accounting for macroeconomic variables in the projection of EAD? If including macroeconomic variables is appropriate, which variables (including those outlined above) should be included to best capture the effects of the macroeconomic environment on the propensity of borrowers to draw down available credit prior to default?

Question E5: Should the Board use different LLEQ equations based on credit limits to reflect differences in behavior across accounts with different credit limits? If so, how should the Board account for the potential for small changes in reported credit limit to lead to large changes in Bank Card EAD when accounts shift from one credit limit equation to another? What are the advantages and disadvantages of each approach?

Question E6: The FR Y-14M instructions allow firms to report any commercially available credit score. This provides flexibility to firms but requires the Board to make assumptions about how the risk of a borrower default compares across different credit score vendors and versions. What adjustments, if any, should the Board make to reported credit score in the Credit Card EAD Model to account for the use of different credit score vendors and versions?

d. Model Integration and Projection

(1) Description

The model projects loss rates by applying the PD, LGD, and EAD estimates produced by the aforementioned models to specific accounts reported on FR Y-14M, Schedule D (Credit Cards), referred to as the "existing portfolio." Accounts that have reached the default threshold defined in this model description as of the start of the projection period, but that have not reached 180 or more days past due and have likely not been charged off by the firm, are considered to have a 100 percent probability of default.[467] As discussed in Section E.ii.d.(2), the Board smooths the impacts of these accounts that are already in default at the start of the projection period. In particular, bank card defaults on these accounts are equally distributed over the second through fifth quarters of the projection period, and charge card defaults on these accounts are equally distributed over the second through fourth quarters of the projection period. In effect, bank card accounts in this position are functionally given a 25 percent probability of defaulting in each of the second through fifth projection quarters, while charge card accounts in this position are functionally given an approximately 33 percent probability of defaulting in each of the second through fourth projection quarters.

For accounts that have not reached the default threshold, the Credit Card PD model coefficients are applied. After the model is applied, projected PD rates are adjusted to produce unconditional projections of PD. This is needed because the model, in each quarter, projects the probability of default for an account given that it has not defaulted in any previous quarter.[468]

[467] Defaults on these accounts are considered as the firm may not have accounted for losses on this account, not having reached the FFIEC's 180-day definition, as described in the introduction to Section E.ii. For accounts that have already reached 180 or more days past due or have been charged off by the start of the projection period, it is assumed that no further losses will be taken.

[468] The probability that an account has not defaulted in a previous quarter is set to the sum of the PD projections in all previous quarters, subtracted from one.

However, this fails to account for the probability the account defaulted previously, after which it cannot default again. To make the adjustment, the Board multiplies the projected PD from the model by the probability that the account has not defaulted in a previous quarter. This adjustment ensures that PD projections accurately measure the likelihood of an account defaulting each quarter, referred to as the "unconditional PD."

Projected unconditional PD[469] is then multiplied by projected EAD to produce a gross loss estimate. For loans that have reached the default threshold as of the start of the projection period, the EAD is set to be equal to the balance at the start of the projection period, as defaulted loans likely do not have the ability to make additional draws. The gross loss estimate is then multiplied by LGD to produce a quarterly net loss estimate. These net losses are then aggregated across all accounts within a sub-portfolio (bank card or charge card) to produce portfolio-level losses and are divided by starting sub-portfolio balances to produce existing sub-portfolio loss rates.

New origination loss rates are projected similarly to existing portfolio loss rates. Portfolio characteristics are assumed to remain constant for new originations compared with fully current[470] accounts in the existing portfolio that are marked as active (not inactive or closed). This is consistent with the supervisory stress test assumption of a constant balance sheet. An exception to the assumption of portfolio characteristics remaining constant is that for new originations, the account age field is reset to zero, as would be expected for new originations. Two new origination loss rate paths are produced—the first starting in the first

[469] Since the Charge Card PD model produces semi-annual projections of PD, in this sentence, "projected unconditional PD" for charge cards refers to the semi-annual projection divided by two for each quarter in the semi-annual period.

[470] Specifically, in this context, "fully current" refers to accounts that are not marked as having positive days past due (on FR Y-14M, Schedule D.1, Line Item 53). Delinquent accounts are excluded, given that new originations, by construction, have not had time to miss payments and become delinquent.

projection quarter and the second starting in the fifth projection quarter. Similar to the existing portfolio, new origination loss rates are calculated separately for bank cards and charge cards.

The above process is applied for all firms reporting data on FR Y-14M, Schedule D (Credit Cards) with sufficient data quality for use in modeling. However, if a firm's reported data is such that less than 50 percent of the total accounts can be scored—due to missing data in fields used for modeling—the reported data are not used to project losses for that firm. Instead, in such a case, the Board applies the existing portfolio and new origination loss rate paths associated with the firm with the 90th percentile loss rate among firms reporting a given sub-portfolio (bank card or charge card) within FR Y-14M, Schedule D, consistent with other stress test models and in line with the stress test policy of conservatism given unavailable data (see Section 2.9 of the Stress Testing Policy Statement).

(2) Support for Model Decisions

The projection of the two new origination loss paths allows for the projection of losses on accounts originated during the projection period. This is necessary to ensure that the model implementation is consistent with the constant balance sheet assumption. The inclusion of two new origination paths balances the goals of simplicity (more paths increase operational complexity and implementation cost) with robustness (new origination loss rates are expected to vary based on when in the projection they are originated), which are two of the principles of supervisory stress testing from the Stress Testing Policy Statement.

The treatment of bank card accounts that are five or more cycles past due—but less than 180 days past due—and of charge card accounts that are 90–179 days past due is intended to smooth the impact of accounts that are already in defaulted status at the start of the projection period. The decision to smooth losses over a period of time is consistent with treatment of other categories of loans in the supervisory stress test. This assumption is made so that losses from such loans are not realized by the firms immediately, in the first projection quarter. Assigning all losses to the first quarter would ignore the inherent uncertainty in the loan resolution process. Furthermore, advancing losses on these loans to the first projection quarter could lead to a large spike in projected losses in the first projection quarter, which has the potential to have unintended effects on the downstream Provisions Model.[471]

Given the decision to smooth losses on defaulted loans, the Board considered the appropriate period of time over which to smooth losses. A longer smoothing period potentially unreasonably mitigates the impact of these accounts, while a shorter smoothing period accelerates losses in the early quarters of the projection. Spreading bank card losses evenly over the second through fifth projection quarters balances these concerns while ensuring that these accounts are treated conservatively, but not unreasonably conservatively. For charge cards, losses are smoothed over the second through fourth projection quarters. This assumption is more conservative than the bank card assumption, and reflects differences in the two products. Since charge cards do not have a credit line and borrowers are expected to pay their balance in full each month, they tend to charge off more quickly upon default—based on the Board's expertise and assessment of supervisory information. Given the faster expected rate of charge-offs for charge cards, losses on these cards are smoothed over a shorter period compared to bank cards.

(3) Adjustments and Data Cleaning Steps

No additional adjustments or data cleaning steps are applied.

[471] *See* Section B in the Aggregation Models Documentation (Provisions Model).

(4) Alternatives

Given that the model integration process is a straightforward application of the PD, LGD, and EAD components, no specific alternative implementations were considered.

e. Retail Loss Aggregation

(1) Description

Retail Loss Aggregation refers to the process by which the Board uses the outputs described in the previous sections to produce final projections of loss dollars. In particular, the process begins with the reported portfolio balances and the projected loss rates described in Section E.ii.d for each quarter for each firm participating in the supervisory stress test and reporting data on FR Y-14M, Schedule D.1 (Credit Cards), for the existing portfolio as well as two projected new origination portfolios. From there, the Board applies a series of calculations and adjustments, described in detail below. The output of the Retail Loss Aggregation process is a final projection of loss dollars for each firm in each sub-portfolio (bank cards and charge cards) in each quarter.

In Retail Loss Aggregation, the projected bank card and charge card loss rates are assigned to the balances of the respective categories of accounts produced by the balance sheet line-item projections calculator based on data reported in FR Y-14Q, Schedule M.1 Balances.[472] In particular, bank card balances are taken from line item 3a, column A (CALBP912), while charge card balances are taken from line item 3b, column A (CALBR659). Existing portfolio loss rates are multiplied by this balance in each of the 13 projection quarters to produce existing portfolio loss dollars. New origination loss dollars are calculated by applying the new origination loss vectors to the projected new origination amounts. New origination amounts in

[472] *See* Section A in the Aggregation Models Documentation (Balances Model).

each quarter are projected as the losses in that quarter on the existing portfolio as well as the losses on any new originations from previous quarters.[473] New originations in the first through fourth projection quarters are assigned the new origination loss rate vector associated with originations in the first projection quarter; new originations in the fifth through thirteenth projection quarters are assigned the new origination loss rate vector associated with originations in the fifth projection quarter. Total quarterly loss dollars are calculated as the sum of losses on the existing portfolio and any new origination portfolio originated by a given point in the projection period. A visual depiction of this process is available in Figure E3:

Figure E3 - Description of Existing and New Origination Loss Rates

			Forecasting (Future) Quarters												
	Vintage	Q_0*	Q_1	Q_2	Q_3	Q_4	Q_5	Q_6	Q_7	Q_8	Q_9	Q_{10}	Q_{11}	Q_{12}	Q_{13}
1	**Existing Portfolio (Q_0 base month)**	base													
2	**New Originations (Q_1 base month)**		base												
3	Interpolated in Retail Loss Aggregation														
4	Interpolated in Retail Loss Aggregation														
5	Interpolated in Retail Loss Aggregation														
6	**New Originations (Q_5 base month)**						base								
7	Interpolated in Retail Loss Aggregation														
8	Interpolated in Retail Loss Aggregation														
9	Interpolated in Retail Loss Aggregation														
10	Interpolated in Retail Loss Aggregation														
11	Interpolated in Retail Loss Aggregation														
12	Interpolated in Retail Loss Aggregation														
13	Interpolated in Retail Loss Aggregation														

In this visual, each row refers to a vintage of new originations, and each column represents a quarter of the supervisory stress test projection period, starting from Q_0, the starting point of the projection. The existing portfolio uses the existing portfolio loss rate (represented by the solid line); the first four quarters of new originations use the first new origination loss rate vector (represented by the dashed line); and the fifth and following quarters of new originations use the second new origination loss rate vector (represented by the dotted line). For example, new originations in the fifth projection quarter use the second new origination vector, where the first quarter of loss rates are applied in the sixth projection quarter, the second quarter of loss

[473] As described in Section E.ii.a, the Board does not consider the probability that an account will close without defaulting.

rates are applied in the seventh projection quarter, and so on. New originations in the sixth projection quarter use the second new origination vector, where the first quarter of loss rates are applied in the seventh projection quarter; the second quarter of loss rates are applied in the eighth projection quarter, and so on.

The above process produces loss dollars for firms reporting data on the FR Y-14M, Schedule D (Credit Cards); however, certain firms that report bank card and/or charge card balances on FR Y-14Q, Schedule M.1 Balances do not report them on the FR Y-14M, Schedule D.[474] For firms not reporting FR Y-14M, Schedule D that are not required to do so, bank card and charge card balances, respectively, are assigned the loss rate paths (of the existing and new origination portfolios) of the firm with the 50th percentile loss rate[475] among firms reporting that sub-portfolio (bank card or charge card) within FR Y-14M, Schedule D.[476] For firms not reporting FR Y-14M, Schedule D that are required to do so, bank card and charge card balances, respectively, are assigned the loss rate path of the firm with the 90th percentile loss rate[477] among firms reporting that sub-portfolio (bank card or charge card) within FR Y-14M, Schedule D, consistent with other stress test models and in line with the stress test policy of conservatism given unavailable data. In either case, if no firm is exactly at the 50th or 90th percentile, respectively, the firm with the loss rate immediately above this level is used, also in line with the stress testing principle of conservatism.

[474] Firms are required to report FR Y-14M, Schedule D (Credit Cards) schedule if portfolio balances are material, as defined in the FR Y-14M instructions. Firms with portfolio balances that are below the materiality threshold have the option of submitting or not submitting the schedule. The Board uses reported data to produce loss estimates for firms whenever possible, even if the reporting institution is below the materiality threshold.
[475] For discussion of the use of the 50th percentile loss rate, *see* Section 2.10 of the Stress Testing Policy Statement.
[476] In this context, "loss rate" refers to total loss dollars divided by initial portfolio balances. Percentiles are calculated by summing the loss rates over the 13 projection quarters.
[477] For discussion of the use of the 90th percentile loss rate, *see* Section 2.9 of the Stress Testing Policy Statement.

Revenue and Loss Sharing Agreements

Finally, the Bank Card Model adjusts losses to reflect certain cases where a covered firm has a partnership agreement with a third party to contractually share a portion of revenues, credit losses, or profits from a specific credit card portfolio. The remainder of this section refers to these partnership agreements using the more general term "revenue and loss sharing agreements" (RLSAs). Firms can reflect RLSAs in more than one way on their financial and regulatory reports;[478] for example, based on the RLSA, a firm may adjust pre-provision net revenue line items to recognize RLSA impacts and may not recognize RLSA impacts in charge-offs, or a firm may choose to recognize third-party loss sharing agreements by reflecting the RLSA impacts in charge-offs and loss reserves.

The Bank Card Model treats RLSAs according to how covered firms report their RLSAs. If a firm reflects the RLSA impacts in charge-offs and loss reserves, and certain conditions are met (described in more detail in Section E.ii.e.(2)), the Board applies an adjustment to reflect the loss share attributable to the third party. Without this adjustment, neither the Bank Card Model nor another part of stress test would account for the third-party loss sharing payments, causing the model to overestimate bank card losses. By contrast, in cases where a firm reports and reserves for bank card losses using pre-provision net revenue line items, rather than by netting the loss sharing payment from credit card losses, the Pre-provision Net Revenue Model already accounts for loss sharing payments related to losses on covered accounts; therefore, further adjustments to the Bank Card Model could lead to inappropriately low projections of bank card losses. However, due to the differences in macroeconomic sensitivity between the Bank Card

[478] An RLSA's loss accounting method is one of the main determinants of whether projected losses from accounts subject to that agreement may need to be adjusted. A firm's method for reporting revenues and non-provision expenses related to RLSAs does not generally impact loss projection but will be discussed in the alternatives section as it may have some impact on the Pre-Provision Net Revenue projections and thus projected pre-tax net income.

Model and components of the Pre-provision Net Revenue Model, the Board is aware that the current adjustment could lead to differential treatment across firms and reduced macroeconomic sensitivity. Therefore, the Board is specifically seeking comment on this assumption; see Section E.ii.e.(4) for more details.

In recent stress tests, the adjustment described in the previous paragraph has been provided via a special data collection. In 2024, the Board proposed collecting information on credit card accounts subject to third-party RLSAs, as well as the contractual and effective loss sharing rate on these RLSAs, on FR Y-14M, Schedule D (Credit Cards).[479] The Board also proposed collecting information on how the firm accounts for losses recovered on the RLSA on this schedule. If the necessary fields are not available on FR Y-14M, Schedule D (Credit Cards) in time for use in a given stress test, the Board will collect this information via a special data collection, as it has in previous stress tests. Loss sharing credits are projected and then subtracted from projected gross losses based on the values reported in these fields. The projected quarterly loss sharing credit is determined based on Equation E9:

[479] The Board proposed collecting information on cards subject to third-party RLSAs and the contractual loss sharing rate via existing fields on the FR Y-14M report, while clarifying that these fields are required to be reported for accounts that are part of third-party RLSAs. *See* "Proposed Agency Information Collection Activities; Comment Request," Board of Governors of the Federal Reserve System, https://www.federalregister.gov/documents/2024/06/21/2024-13798/proposed-agency-information-collection-activities-comment-request. If the necessary fields are not available on FR Y-14M, Schedule D (Credit Cards) in time for use in a given stress test, the Board expects to collect this information via a supplementary data collection.

Equation E9 - Loss Sharing Credit

$$loss\ sharing\ credit_t\ =\ \%bal\ RLSA\ \times LSR_{effective} \times gross\ loss_t,$$

where:

- $\%bal\ RLSA$ is the share of a firm's bank card[480] balance reported immediately prior to the projection period that is associated with accounts subject to an RLSA agreement with a third party[481] in the month immediately prior to the start of the projection period;
- $LSR_{effective}$ is the effective loss sharing rate among accounts subject to RLSAs over the year prior to the start of the projection period. This is calculated as the total loss share credits for accounts reported over the relevant year,[482] divided by the total gross charge-offs reported on FR Y-14M, Schedule D.1, Line Item 62 among bank card accounts subject to a revenue and loss sharing agreement with a third party over that same year as reported on the relevant reporting form;[483] and
- $gross\ loss_t$ is the total losses projected on a firm's bank card portfolio based on the calculations in this Retail Loss Aggregation section, which reflects losses gross of loss sharing for accounts subject to RLSAs.

The projected RLSA credits are subtracted from projected losses to produce a final projection of credit card losses in each quarter for each firm that reports charge-offs and provisions net of third-party partner loss sharing payments. These adjusted quarterly losses are used in downstream calculations to produce estimates of provisions.[484]

(2) Support for Model Decisions

The Retail Loss Aggregation process produces loss estimates in a simple, consistent manner across all retail portfolios. This ensures adherence to the Stress Testing Policy Statement

[480] As there are no reported charge cards covered by revenue and loss sharing agreements with third parties that meet the conditions for the adjustment, this adjustment is made to bank cards only. If this changes in the future, the Board will consider updating the adjustment to account for charge cards as well as bank cards.
[481] From either the FR Y-14M, if and when the changes to the instructions are finalized, or the special data collection, otherwise, as described above.
[482] From either the FR Y-14M, if and when the changes to the instructions are finalized, or the special data collection, otherwise, as described above.
[483] The Board's special data collection used in recent supervisory stress test exercises instructs firms to annualize loss share credits from partnerships that begin mid-year for consistency with loss share credits that were in effect for the full year.
[484] *See* Section B in the Aggregation Models Documentation (Provisions Model).

principles, including simplicity, consistency, robustness, and the assumption of a constant balance sheet throughout the forecast period.

Revenue and Loss Sharing Agreements

The RLSA adjustment is an important component of the Retail Loss Aggregation process because it improves the consistency of the treatment of third-party loss sharing payments across firms. Without the adjustment, certain third-party payments associated with RLSAs would not be incorporated into the stress test projections—leading to the over-projection of credit card losses—while for other firms these payments would be considered. However, the RLSA adjustment requires two key assumptions: the determination of which agreements are subject to the adjustment and the calibration of the loss sharing rate. As described below, the Board has considered certain alternative implementations of the RLSA adjustment that would eliminate the need to make some or all of these assumptions. The two assumptions are discussed below.

Determination of Agreements Subject to the Adjustment

As mentioned above, firms can report RLSA impacts on credit losses, loan revenues, and expenses in multiple ways. In cases where a firm reports charge-offs and loss reserves and does not reflect the third-party loss sharing payments associated with the RLSA in these charge-offs and loss reserves, no adjustment is made to the Bank Card Model output. This is because in these cases, firms reflect the net revenue impacts of the RLSA in pre-provision net revenue reporting.[485] As a result, the Pre-provision Net Revenue Model would generally capture the payments from these agreements based on historical payment levels; in certain cases, the model would produce projections that account for increased loss sharing based on the macroeconomic scenario.[486] If the Board were to apply an adjustment to the Credit Card Model for these firms,

[485] For example, firms may report these in an "all other" component of pre-provision net revenue.
[486] *See* the Pre-Provision Net Revenue Model Documentation.

this adjustment would cause these third-party loss sharing payments to be double-counted, once in the Credit Card Model and again in the Pre-Provision Net Revenue Model. However, for cases in which (1) agreements include both a revenue sharing and loss sharing component[487] and (2) the firm reflects revenue sharing in pre-provision net revenue but accounts for loss sharing via reductions in provisions (reflecting the agreement in charge-offs and reserves), the third-party loss sharing payments would not be considered anywhere in the stress test models. Therefore, in the case where a firm accounts for loss sharing via reductions in provisions, the Bank Card Model applies an adjustment to reduce projected losses by the amount of the projected third-party loss sharing payments.

Calculation of Loss Sharing Rate

As described in Section E.ii.e.(1), the Board calibrates the effective loss sharing rate for the purposes of this adjustment as the total loss sharing credits paid over the previous year divided by the total gross charge-offs on accounts subject to RLSAs over the previous year, and only for RLSA contracts that are in effect as of the last day of the calendar year. In effect, this assumes that the effective loss sharing rate throughout the projection horizon will remain equivalent to its level over the year prior to the start of the projection period.

This assumption aligns with the Stress Testing Policy Statement principle of simplicity. This simple assumption is reasonable, despite that it does not account for certain agreements which may have terms that change over time, have conditions such as a loss sharing threshold or cap, or have a minimum loss sharing payment—which could cause the loss sharing rate to be

[487] The Board determined that the RLSA loss adjustment should not be applied in the case of loss sharing only agreements that are not paired with a revenue sharing component due to concerns that the firm would face heightened counterparty credit risk with such contracts. Based on data collections to date, the Board has assessed that it is unlikely for such a loss sharing only agreement to exist. If such agreements become material, the Board may consider revisiting the treatment of loss sharing agreements that do not include a revenue sharing component.

higher or lower during the scenario than its historical levels or to vary at different points over the scenario. Based on the Board's experience and knowledge of individual firms' agreements, individual RLSAs can be complex and have bespoke conditions such that it is challenging to account for the unique characteristics of each agreement in a truly consistent, granular and simple manner. This is because the contractual terms of each RLSA may vary substantially, even for a given firm with multiple RLSAs. Furthermore, current data collections and forms only enable the Board to adjust losses to account for RLSAs at the portfolio level, rather than at the account or agreement level. The reporting forms could be expanded to capture more granular details about the agreements; however, this would result in a substantial reporting burden on firms and require a complex modeling framework to capture exactly.

To minimize the challenges arising from the unique terms of each agreement, the Board instead relies on the historical effective loss sharing rate to calibrate the RLSA adjustment. Relying on loss sharing credits over the previous year smooths out idiosyncrasies that can arise when considering the loss sharing rate over shorter periods, such as the previous month. This is particularly important because loss sharing payments may be paid in a different month from the charge-off date, or may be paid in blocks at longer frequencies, such as each quarter or each year. Additionally, using a full year to calibrate the adjustment smooths out any idiosyncrasies, including seasonality in credit card losses (as noted in Section E.ii.a.2, credit card default risk tends to be seasonal) or loss sharing that may cause the effective loss sharing rate to be different in some months than others. Based on these factors, the Board deems the previous year's effective loss sharing rate an appropriate calibration for sharing rates on loss projections in the hypothetical stress scenario.

(3) Adjustments and Data Cleaning Steps

Generally, no data adjustments are needed for this step. However, if a firm's submitted data in a sub-portfolio are too deficient to produce a supervisory loss estimate, the Board assigns a high (90th percentile) loss rate, as discussed above, to the portfolio balances based on supervisory projections of bank card or charge card losses, respectively, for other firms.

(4) Alternatives

A range of alternatives is theoretically available both for determining the level of new originations and the treatment of missing data and immaterial portfolios. However, the chosen approach is consistent with certain assumptions applied broadly in the supervisory stress test: importantly, the assumption of a constant balance sheet through the projection period and the treatment of missing data and immaterial portfolios. The Retail Loss Aggregation framework is chosen to produce reasonable, consistent projections that are consistent with the Stress Testing Policy Statement.

Revenue and Loss Sharing Agreements

The Board's RLSA adjustment accounts for a specific case where a firm accounts for loss sharing payments by reducing provisions. Because the Credit Card Model would not otherwise reflect loss sharing payments, failing to adjust for this case would implicitly and unreasonably assume that this firm receive no loss sharing payments in the projection horizon. When firms instead account for loss sharing payments via pre-provision net revenue, the pre-provision net revenue models generally reflect the existence of these loss sharing payments in some form. This is because the Board's regression and nonparametric models for interest income, interest expense and noninterest expense subcomponents incorporate historic trends as reported by firms. In these cases, firms often report credit loss provisions exclusive of any loss sharing payments related to existing agreements; given that the Credit Card Model does not automatically account for loss sharing payments, and the loss sharing payments are reflected in projections of pre-provision net revenue, no adjustments are applied in this case. However, the Board is aware that agreement terms and reporting practices vary, and—as a result—it is likely that the current RLSA adjustment does not fully or consistently address differential treatment of RLSA impacts across firms. Thus, the Board has considered additional enhancements to the current adjustment to better align with the Stress Testing Policy Statement principles of consistency and comparability.

One example of a situation in which the current treatment may lead to inaccurate projections is a firm which has an agreement with a third-party to share profits on a bank card portfolio, and reports this profit-sharing payment in pre-provision net revenue via the "noninterest income all other" component. The Pre-provision Net Revenue Model projects "noninterest income all other" based on the median of recent historical periods. However, in practice, RLSA profits can be sensitive to macroeconomic conditions, as profits on credit card portfolios (and thus profit-sharing payments) tend to decline during periods of economic stress. Because the Pre-provision Net Revenue Model projects "noninterest income all other" based on the median of recent historical periods, the current RLSA treatment may conflict with the principle that supervisory projections should be able to evaluate the impact of severe economic stress, as discussed in the Stress Testing Policy Statement.

It is challenging to design and apply an adjustment in the above case because the existing data collection is insufficient to capture the necessary information and data to do so. Specifically, to address the above example, the Board would need data on total portfolio balances subject to RLSA, total income and expenses tied to RLSA, as well as the corresponding specifics of reporting geography. Additionally, information on portfolio-level contractual or effective loss and revenue sharing rates, and provision build if applicable, could then be used along with an appropriately macro-sensitive net revenue estimation to ensure that the implied revenue, expense and loss share amount included in pre-tax net income projections is appropriately responsive to stress conditions.

Another example of where the current approach lacks granularity involves a situation where a firm has multiple third-party agreements, each with unique terms. Agreements with individual third parties may carry different share rates and include contract-specific features such as thresholds and/or caps that would need to be captured in revenue, loss and profit calculations. To account for this, a second, more complex, alternative is to apply the adjustments discussed above to individual third-party agreements, as opposed to the portfolio level. This more granular approach could allow for a more accurate capture of the details of each partnership in the projection (and possibly increase the macro-sensitivity of the estimates), but at the same time would significantly increase reporting burden on firms. In addition, more complex or bespoke details of agreements could be hard to capture in a concise and consistent manner, so even an agreement-level data collection may not fully capture all relevant contract features. Due to the wide range of agreement terms, the Board seeks comment on the minimum level of detail and agreement features that should be captured in the reporting forms and in the stress test models.

In line with the alternative adjustments contemplated above, the Board has considered expanding the data collection to collect additional information associated with RLSAs, including but not limited to the following:[488]

[488] If the model applies the adjustment, and designs the data collection, at the portfolio-level, firms that have RLSAs that span different accounting treatment and regulatory reporting would need to first group together the agreements with similar reporting and then provide the details on revenue, loss and provision components, corresponding partner share rates, and location of FR Y-14 and FR Y-9C reporting separately for each grouping. If the model applies the adjustment, and the Board designs the data collection, at the agreement level, each agreement would be reported separately.

- Quantitative details on individual revenue components (such as interest income, interest expense, noninterest income, and noninterest expense), net charge-offs, provision build, average partner share rates, and average contractual share rates;
- The specific FR Y-9C and FR Y-14 revenue and expense line items that are impacted by sharing agreements; and
- Accounting practices for recognizing and provisioning for losses.

While more granular data collections would increase the reporting burden on firms and likely increase model complexity, they would enable the Board to adjust pre-provision net revenue projections to explicitly reflect the impact of RLSA agreements and improve the macroeconomic sensitivity of supervisory pre-tax net income projections under stress.

(5) Questions

Question E7: Given the wide range of contractual terms and accounting practices used by firms to share revenues and losses on credit cards with third parties, how can the Board best align the treatment of RLSAs with the principles in the Stress Testing Policy Statement?

Question E8: The Board is seeking feedback on creating an approach that harmonizes the treatment of RLSAs across agreement types and reporting practices. For example, should the Board expand the adjustment to capture agreements where firms report provisions gross of any loss sharing payments? If so, what other changes should be made? The Board is also seeking feedback on whether a data collection and adjustment conducted at the portfolio level is sufficient to account for RLSAs, as opposed to the agreement level.

Question E9: Should the Board consider any alternative adjustments that would allow more agreements to be captured while limiting additional data collections? If so, which types of adjustments should be considered?

Question E10: Are there additional indicators or factors that the Board should consider to better capture revenue and loss sharing agreements in supervisory projections? For example, *how should the Board balance the benefits of improved RLSA estimation via alternative adjustments against the additional burden of data collection and model complexity? Which reporting form should the Board use to incorporate those additional factors, and how could they be incorporated into the model?*

Question E11: Are there any other types of third-party agreements related to credit cards that are not captured by the current adjustment or the alternative adjustments contemplated above, that should be captured by the Board's models? If so, how should the Board reflect these third-party agreements on reporting forms and account for them in the supervisory stress test?

iii. Key Assumptions for the Credit Card Model

a. Treatment of Continuous Variables in the Model

Continuous variables are variables that take a numerical value, such as utilization, credit score, and credit limit.[489] While there is no fundamental problem with including continuous variables in a regression model, challenges arise when the impact of a variable is not consistent at every point in its distribution. As noted earlier, for example, it is plausible that increasing utilization from 5 percent to 10 percent has a small impact on default compared to increasing it from 90 percent to 95 percent; it is important to provide flexibility in the model for it to account for these differential (or non-linear) effects. Without this flexibility, the model would be forced to treat an increase in utilization from 5 percent to 10 percent, which likely in reality only has a minor impact on the risk of default, as increasing the probability of default by the same amount as an increase in utilization from 90 percent to 95 percent, which pushes a borrower close to their credit limit and therefore likely has a much larger impact on the risk of default for that account.

[489] In addition to continuous variables, the Credit Card Model uses categorical variables, such as product type, where accounts are defined as belonging to different categories.

A simple, flexible implementation to account for non-linear effects would involve binning, as defined in Section E.ii.a.(4). This strategy is used for the Charge Card PD Model, and has in the past been used throughout the Credit Card Models. Binning is easy to implement and produces generally reasonable projections on average, especially in cases in which changes in variables are especially impactful at certain values. However, binning continuous variables can create “cliff effects,” where seemingly immaterial changes in variable values have sizable impacts on projections if they move an account from one bin to another. These cliff effects raise concerns that the model may not accurately reflect changes in risk at the boundaries of the bins that correspond to the changes in risk estimated by the model. These cliff effects are of particular concern in the Bank Card Model, due to the size of the bank card portfolio and the high materiality of bank card losses in the supervisory stress test. As a result, binning is not used in the Bank Card PD or EAD Models.

An additional factor to consider is the potential for binning to unintentionally incentivize firms to change lending decisions based on the locations of the bins. This is especially concerning for the treatment of credit limit in the Bank Card PD Model—which is determined by the lender—as it is possible that a binned model will incentivize the bunching of credit limits just above or below the cut-off point to reduce loss projections. Since charge cards generally do not have preset credit limits, this particular concern is less relevant for the Charge Card PD Model.

In the Bank Card PD and EAD Models, linear splines are used to account for non-linearities in the impact of continuous variables. See Section E.ii.a and Section E.ii.c for more information on support for the use of splines in these models.

b. Extensions of Projected PD and EAD through 13 Quarters

As stated in Section E.ii, while the Credit Card Model is used to project loan losses over a 13-quarter period, the model is estimated over shorter horizons. In particular, the Bank Card PD Model is estimated over nine quarters; the Charge Card PD Model is estimated over ten quarters; and the Bank Card EAD Model is estimated over eight quarters.

The shorter horizons over which the models are estimated creates the potential for inaccurate projections if there are large differences in the behavior of accounts in the periods beyond the end of the horizon over which the models are estimated. For instance, if accounts are systematically more or less likely to default ten to thirteen quarters after the reference period than they are to default nine quarters after the reference period, then the model projections could be inaccurate.

However, while this concern is theoretically plausible, there is not strong economic intuition for the idea that default rates or LLEQ should be notably different in these periods compared to the last quarter incorporated into the model calibration. To understand why this is the case, it is important to understand the factors for which the projection period variables account. First, since it takes time for an account to proceed from current to defaulted status, accounts are less likely to immediately default than they are to default in a later quarter; conversely, for delinquent accounts, accounts that survive the first few quarters while already delinquent have survived the acute distress and are less likely to default going forward. Second, as accounts continue to proceed through the first series of quarters, they become more seasoned; as demonstrated by the PD and EAD models, seasoned accounts are broadly less risky than younger accounts. While the impact of seasoning is accounted for in the account age variables in the PD and EAD models, it is plausible that the projection period variables also partially capture the impacts of seasoning.

While these two factors are both potentially meaningful, justifying the use of different equations for different horizons and variables for projection quarter within the individual equations, the impacts of both factors should plateau over time. This is because the importance of time for an account to proceed to default or survive the acute delinquency diminishes as more time elapses since the start of the projection period; meanwhile, the incremental impact of account age (to the extent that the projection period variables account for seasoning impacts) on both PD and EAD diminishes over time. Given these considerations, the Board believes it is reasonable to apply estimates from the eighth through tenth projection quarters (depending on the model) to project losses in the additional projection quarters.

While the incremental impacts of accounting for additional quarters in the estimation of the model are small, the costs are more meaningful. As the projection window expands, the sample size decreases; this is especially problematic for delinquent accounts, many of which have already defaulted in the early projection quarters. The reduction in data availability over longer time horizons reduces the precision of estimates, potentially leading to inaccuracy.

(1) Questions

Question E12: The Board seeks comment on whether to continue to use models estimated on shorter horizons to project losses over 13 quarters, as opposed to developing a model that is estimated on a 13-quarter horizon.

c. Representativeness of Estimation Data

To produce accurate, reliable projections of credit card losses under a hypothetical scenario, it is important that the data used to estimate the model is representative of the data on which the model is projecting losses. In the Bank Card PD and Bank Card EAD Models, the data used to estimate the model parameters covers a broad period of time ranging from the peak of the 2008 financial crisis through the COVID-19 pandemic, and includes quarters through the second quarter of 2023 to account for behavior in the credit card market during the period of relatively high inflation and increasing interest rates in 2022 and 2023. The portfolio data used is the Bank Cards Data, which reflects the same population of accounts as those in the supervisory stress test exercises. Based on these factors, the Bank Card PD and EAD models rely on representative data.

The Board assessed considerations regarding the inclusion of data in the model during periods covered by the COVID-19 pandemic. In particular, there are unique challenges associated with accounting for the behavior of the portfolio during this period. The unemployment rate initially increased at a historic pace and then declined sharply from its peak. While historically, high or increasing unemployment is associated with higher credit card default rates, during this period, default rates did not increase, in part due to government support programs offered at that time.

Academic research corroborates the view that the economic distortions in 2020 and the years following are significant, and that the observed relationships between the economic environment and borrower behavior during this period are unique to it. For example, Stock and Watson (2025) find that the COVID shock was notable, but had "largely disappeared by late 2022."[490] This finding raises concerns that if data covering 2020-2022 are used to estimate the model coefficients, these coefficients may be impacted by the distortions that caused these unusual observed relationships.

[490] Stock, J. and M. Watson (2025). "Recovering from COVID," NBER working paper 33857.

Despite these concerns, ending the estimation in 2019 could potentially lead to model parameters that do not reflect the current portfolio, as such a model would exclude recent periods. This could lead to model projections that do not accurately reflect the true level of risk. To account for concerns about distortions during the COVID-19 pandemic period, while ensuring that recent data is incorporated when estimating the model coefficients, the Board applies a treatment in the PD model to observations in 2020 and 2021 to account for these distortions.[491] More information on this treatment is available in Section E.ii.a.

The Board determined that the EAD model, which does not contain any macroeconomic variables, was not significantly distorted by the inclusion of pandemic-era data. Therefore, the Board determined not to apply any specific treatment in the EAD model.

The Charge Card PD model relies on a representative sample of U.S. households with charge cards. Based on analysis of the Charge Card Data, account and borrower characteristics appear consistent with the FR Y-14M data when comparing the distributions of key variables. However, unlike the Bank Card PD Model, the Charge Card PD Model does not incorporate data from more recent periods. This is because of the complications, as described above, associated with incorporating the pandemic data into the model. While these changes are accounted for in the Bank Card PD Model, the complexity of the adjustment is not justified in the simpler Charge Card PD Model, which applies to a smaller and less material portfolio.

While not including more recent data creates the risk that the model does not account for any changes in the charge card environment in the intervening years, in practice, the model continues to meet the Board's ongoing monitoring standards in recent periods when using back-

[491] The treatment is applied to 2020 and 2021 observations, but not those from 2022, based on the Board's analysis that distortions in the credit card market mostly were resolved by the end of 2021. By 2022, changes in the unemployment rate had returned to their normal pre-pandemic range.

testing analysis, which tests model performance compared to historical performance using actual historical portfolio and macroeconomic data. Given that there is no sign of deterioration in model performance, the model does not appear to be limited by any lack of representativeness; for this reason, the Board has assessed that the estimation data for the Charge Card PD model is appropriate.

Finally, the LGD parameters for both bank cards and charge cards are based on historical data from the 2008 financial crisis period. Given that account management and borrower populations have changed in the intervening years, it is possible that the LGD estimates are no longer reflective of the population of account holders in recent periods. Nevertheless, the model applies a conservative approach to account for the uncertainty in how much recovery rates would deteriorate during a future economic downturn. Absent evidence that recovery rates would be notably different in a future economic stress event, the Board continues to calibrate LGD based on the 2008 financial crisis period.

F. Auto Model

i. Statement of Purpose

The Domestic Auto Loan Loss Model (alternately called the "U.S. Auto Model" or "Auto Model") is used to project loan losses and provisions on domestic consumer loans held for investment at amortized cost that are extended for the purpose of purchasing new and used automobiles and light motor vehicles, as defined by the FR Y-9C. The Auto Model's calculations are included in the "other consumer" category of projected aggregate loan losses that contribute to the calculation of pre-tax net income. The Board estimates the Auto Model using historical data on auto payment status and loan losses, loan characteristics, and economic conditions. The model projects losses at the loan level with an expected-loss framework—as described in Section III.A in the Enhanced Transparency and Public Accountability Proposed Rule—using data on firm-reported loan characteristics from the FR Y-14Q and economic conditions defined in the Board's supervisory stress test scenarios.[492] All firms with material portfolios are required to report FR Y-14Q, Schedule A.2 (U.S. Auto Loan).[493] Firms with portfolio balances that are below the materiality threshold have the option of submitting or not submitting the schedule.

The expected-loss framework consists of a PD component, an LGD component, and an EAD component. Each of these components is projected using models, detailed throughout this model description. The model projects PD, LGD, and EAD by applying the model parameters, along with some adjustments described in this model description, to specific loan segments from the FR Y-14Q regulatory report. The model outputs projected losses under the hypothetical scenario.

ii. Model Description

The Auto Model projects loan losses and provisions on auto loans, as defined in the FR Y-9C, using an expected-loss framework.

The Auto PD Model, described in detail in Section F.ii.a, estimates the probability that a loan transitions its status from either a current or delinquent state to default status, given the characteristics of the loan and borrower and macroeconomic variables, including house prices and the unemployment rate. The Board defines auto loans as in default, for modeling purposes of the supervisory stress tests, if the vehicle is in repossession or if the loan is 120 days or more

[492] The Federal Reserve specifies loan segments in the FR Y-14Q, Schedule A.2 (U.S. Auto Loan).

[493] FR Y-14Q Instructions, at 1–2. For firms subject to category IV standards, material portfolios are defined as those with asset balances greater than $5 billion or with asset balances greater than ten percent of Tier 1 capital on average for the four quarters preceding the reporting period. For firms subject to category I, II, or III standards, material portfolios are defined as those with asset balances greater than $5 billion or asset balances greater than five percent of Tier 1 capital on average for the four quarters preceding the reporting period. Id. at 2.

past due, in bankruptcy, or charged off.[494] The model estimates the probability that a loan defaults in a quarter using the Credit Bureau Data. Because the relationship between the PD and its determinants can vary with the payment status of the loan, the Board estimates two separate transition models for loans that are current and for those that are delinquent.[495] The probability that a loan defaults is modeled separately for each projection period using a binomial logistic regression,[496] a common model structure for estimating probability of default. Mathematically, the Auto PD Model is shown in Equation F1:

Equation F1 – Auto PD Model Specification

$$PD_{i,t} = f\left(X_{i,t}, Z_t\right)$$

where:

- i represents the loan;
- t represents time;[497]
- $PD_{i,t}$ represents the probability of default for loan i in time t;
- $X_{i,t}$ represents loan and borrower characteristics used in the model, such as origination credit score and loan age; and
- Z_t represents macroeconomic variables used in the model.

The Board models the LGD for auto loans as a function of loan as well as borrower characteristics and macroeconomic variables. The historical data used to estimate this model are segment-level data provided by firms in FR Y-14Q, Schedule A.2 (U.S. Auto Loan). The model

[494] *See* Section F.ii.a for more information on this definition.
[495] The Board defines auto loans as current, for modeling purposes of the supervisory stress tests, if they are no more than 29 days past due and as delinquent if they are between 30 and 119 days past due (unless meeting the default criteria, for instance if subject to bankruptcy or repossession). This definition of delinquency is consistent with other sources; for example, delinquency is reported to credit bureaus once a loan becomes 30 days delinquent.
[496] A binomial logistic regression is a mathematical functional form with a single outcome variable (in this case, default or no default) that is smooth and bounded at zero and one. Because of these features, the output of a binomial logistic regression can be interpreted as a probability.
[497] Because the estimation data are only available on a semi-annual basis for some portion of the history, rather than a quarterly basis, the model estimates the probability that a loan will default over a given six-month period.

estimates the LGD for defaulted loans within a segment using a linear regression model, shown in Equation F2:

Equation F2 – Auto LGD Model Specification

$$\mathrm{LGD}_{k,\mathrm{t}} = f(X_k, Z_t)$$

where:

- k represents the segment;
- t represents time, measured quarterly;[498]
- $\mathrm{LGD}_{k,\mathrm{t}}$ represents the loss given default for segment k at time of default quarter t;
- X_k represents characteristics of the segment k, such as product type, loan-to-value ratio (LTV), and loan age; and
- Z_t represents the macroeconomic variables included in the equation.

The model then projects LGD by applying coefficient estimates to segment-level data from the FR Y-14Q. See Section F.ii.b for more information about the LGD model.

The Board bases the EAD for auto loans on the pattern of amortization of loans that ultimately defaulted in the Credit Bureau Data, as reflected in Equation F3:

Equation F3 – Auto EAD Model Specification

$$\mathrm{EAD}_{s,k,\mathrm{t}} = \mathrm{UPB}_{s,k,0} * PR_{s,k,t}$$

where:

- s represents the delinquency status of the loan as of the start of the projection period (t=0);
- k represents the age of the loan as of the start of the projection period;[499]
- t represents time to default, measured semi-annually;
- $\mathrm{EAD}_{s,k,\mathrm{t}}$ represents the EAD for delinquency status s and loan age segment k at the default time t;
- $\mathrm{UPB}_{s,k,0}$ represents the unpaid principal balance for delinquency status s and loan age segment k as of the start of the projection period; and

[498] Unlike other model components, data used to calibrate the LGD model are available quarterly, rather than semi-annually, so a quarterly model is used.
[499] "Start of the projection period" refers to the starting period from which projections are made. For instance, if a loan is projected to default in the sixth projection quarter, the EAD model projects the balance of a loan at the time of default, given its characteristics six quarters prior. In this example, the "reference period" would be six quarters prior to the default date.

- $PR_{s,k,t}$ represents a paydown ratio for delinquency status s and loan age segment k at the default time t. $PR_{s,k,t}$ is estimated as a function of loan age and delinquency status as of the start of the projection period.

See Section F.ii.c for more information about the calculation of EAD.

The model projects loss rates by applying the PD, LGD, and EAD equations to specific loan segments from FR Y-14Q, Schedule A.2 (U.S. Auto). This process is described in detail in Section F.2.d. Loss rate paths are produced both for the portfolio of loans reported on the FR Y-14Q at the start of the stress test projection period (the "existing portfolio") as well as projected portfolios of new originations.[500] These loss rates are applied to the balances reported on FR Y-14Q, Schedule M (Balances) through the Retail Loss Aggregation process (see Section F.ii.e for more information). Total loss dollars are projected as the sum of the losses on the existing portfolio plus the projected losses on projected new origination balances[501] during the projection period.

Each of the model components are estimated using the auto portfolio data sources described above, along with macroeconomic data as described in this model description.

A detailed description of each of the model components is below. First, the structure, input data, and variables used to define the model are described. Next, support for the modeling decisions, including the model structure and the individual variables included in the model is provided. Then, the data cleaning process and any adjustments applied to the input data are

[500] New originations are assumed to have the same risk characteristics as the existing portfolio, except that the loan age for all loans is reset to 0 and the delinquency status is reset to current. This ensures consistency with the supervisory stress test assumption that firm balance sheets will remain constant through the projection. *See* Section 2.7 of the Stress Testing Policy Statement for more information.
[501] Projected new origination balances are calculated to be equivalent to the previous quarter's losses plus the projected principal payments in the previous quarter, consistent with the supervisory stress test assumption that firm balance sheets will remain constant through the projection.

detailed. Finally, alternatives to the chosen modeling approaches are discussed, along with questions to solicit feedback from the public.

a. Probability of Default Model

(1) Description

The Auto PD Model estimates the probability that a loan transitions from either a current or delinquent status to default status, given the characteristics of the loan and borrower and macroeconomic variables, including house prices and the unemployment rate. The Board defines auto loans as in default, for modeling purposes of the supervisory stress tests, if the vehicle is in repossession or if the loan is 120 days or more past due, in bankruptcy, or charged off. The 120 days past due threshold is consistent with the Federal Financial Institutions Examination Council's Uniform Retail Credit Classification and Account Management Policy,[502] which states that "closed-end retail loans that become past due 120 cumulative days…from the contractual due date should be classified Loss and charged off." Loans to borrowers in bankruptcy or charged off, meanwhile, have been recognized to lenders as losses, making it appropriate to treat these loans as in default as well.

To estimate the Auto PD Model, the Board uses the Credit Bureau Data, as described earlier in this model description. The Credit Bureau Data contains detailed credit-report data for individuals and covers a nationally representative random sample of U.S. consumers with a both a social security number and credit file. The Credit Bureau Data includes multiple auto loans for each consumer in the panel. Each observation includes loan and borrower characteristics,

[502] *See* Federal Financial Institutions Examination Council, Uniform Retail Credit Classification and Account Management Policy, June 12, 2000, https://www.federalregister.gov/documents/2000/06/12/00-14704/uniform-retail-credit-classification-and-account-management-policy.

including credit score, payment status,[503] origination date, original loan amount, and current balance. Data are available at a semi-annual frequency over most of the sample period and are available at a quarterly frequency in more recent years. Due to the large size of the Credit Bureau Data, the Board uses a random 10 percent sub-sample of the data to fit the Auto PD Model; details on the sampling and data cleaning process are available in Section F.ii.a.(3). The Board uses data covering 2000 through 2019 to fit the model.[504]

Credit bureau data have become increasingly popular among economists in recent years, due to the breadth and depth of information contained in them. For an overview of credit bureau data, and its use cases in economic modeling, see Gibbs et al. (2025).[505]

Using the Credit Bureau Data, the model defines auto loans as current, delinquent, or in default based on loan characteristics. In addition to the default definition outlined earlier in this section, the Board defines auto loans as current, for modeling purposes of the supervisory stress tests, if they are no more than 29 days past due, and defines auto loans as delinquent if they are between 30 and 119 days past due (unless subject to bankruptcy or repossession), consistent with general industry practice.[506] With these statuses defined, the discrete-time[507] hazard rate of auto loans is calculated as shown in Equation F4:

[503] To mitigate the risk that the semi-annual frequency does not capture monthly payment dynamics, each observation includes the payment status of a given loan for each of the previous 24 months.
[504] A discussion of the choice of the estimation sample period is available in Section F.iii.a.(3).
[505] Gibbs, Christa, Benedict Guttman-Kenney, Donghoon Lee, Scott Nelson, Wilbert Van der Klaauw, and Jialan Wang. "Consumer credit reporting data." Journal of economic literature 63, no. 2 (2025): 598-636.
[506] Notably, loans are reported as delinquent to credit bureaus when they reach 30 days past due.
[507] "Discrete-time" refers to the model's analysis of the likelihood of default over predefined intervals (in this case, semi-annual periods), as opposed to treating time as a continuous variable.

Equation F4 – Auto PD Hazard Model

$$P_{i,t} = \Pr\left[T_i = t \middle| T_i \geq t, X_{i,t}, Z_t\right]$$

where:

- i represents the loan;
- t represents time;[508]
- $P_{i,t}$ represents the probability of default in time t, given that the loan has not defaulted prior to time t;
- T_i represents the default time of a loan;
- $X_{i,t}$ represents loan and borrower characteristics, such as credit score and loan age; and
- Z_t represents a vector of macroeconomic variables used in that equation.

Mathematically, this hazard rate is specified as a logistic function. The model is specified using separate equations for loans that start as current and loans that start as delinquent. Separately for current and delinquent loans, the equation generates a probability of default in each of five time horizons ("performance periods"), corresponding to the second, fourth, sixth, eighth, and tenth projection quarters.

The loan characteristics used in the models are chosen to account for the most important risk factors in the portfolio. The Auto PD Model is also designed with the structure of FR Y-14Q, Schedule A.2 (U.S. Auto) in mind. Unlike the FR Y-14 schedules used to model retail first lien mortgages, home equity exposures, and credit cards—which collect data at the loan-level (meaning each observation is a loan) —the schedule used for domestic auto loans is collected at the segment-level, where firms report detailed summary statistics for each category (or segment) of loans; segments are defined based on loan and borrower characteristics such as origination credit score, loan age, and delinquency status. The schedule is developed to align with the stress

[508] Because the estimation data are consistently available only a semi-annual basis rather than a quarterly basis, the model estimates the probability that a loan will default over a given six-month period.

testing principles of simplicity as well as robustness and stability; the segments are designed to be sufficiently granular to identify portfolios with different levels of risk, but not so granular to capture every distinction. The constraints based on the structure of the schedule limit both the choice of variables as well as the granularity of the segments created from the variables.

The full specification of the Auto PD Model is available in Table F1. An explanation of the individual parameters and variable descriptions is available in Section F.ii.a.(2).

Table F1 - PD Model Specification

		Current Segment		Delinquent Segment	
Parameter	Variable Description	Estimate	Std. Error	Estimate	Std. Error
Intercept		-3.3221	0.0080	-0.6257	0.0175
Performance Period	1-6 months	--	--	--	--
	7-12 months	0.4671	0.0039	-0.5188	0.0066
	13-18 months	0.5380	0.0040	-0.7142	0.0076
	19-24 months	0.5673	0.0042	-0.8738	0.0085
	25-30 months	0.5634	0.0044	-1.1005	0.0096
Loan Age	Less than 1yr.	--	--	--	--
	Between 1 and 2 yrs	-0.0478	0.0077	-0.4665	0.0167
	Between 2 and 3 yrs	-0.1534	0.0077	-0.6655	0.0166
	Greater than 3 yrs	-0.4053	0.0077	-0.9642	0.0163
Origination Risk Score	<=560	--	--	--	
	561-620	-0.5153	0.0029	-0.2147	0.0058
	621-660	-1.0713	0.0034	-0.4338	0.0075
	661-720	-1.7555	0.0036	-0.6736	0.0089
	720+	-3.1801	0.0049	-1.0270	0.0144
Joint Application		-0.1583	0.0023	-0.1517	0.0049
Seasonality	Perf period in Jan-Jun	-0.0919	0.0023	-0.1058	0.0049
Ever30	Ever 30+DPD in the past 12 months	0.9497	0.0030	--	--
Delinquent	30-59DPD	--	--	--	--
	60-89DPD	--	--	0.7028	0.0059
	90-119DPD	--	--	1.1712	0.0093
UR	Unemployment rate (UR)	0.0317	0.0006	0.0171	0.0012
YoY change	UR	0.0399	0.0011	0.0260	0.0020
	UR & orig. risk scr 661-720	0.0530	0.0023	--	--
	UR & orig. risk scr>720	0.0614	0.0032	--	--
	HPI	-0.0048	0.0002	--	

Where the parameters are defined as follows:

- "Intercept" refers to the intercept of the regression equation;

- "Performance Period" refers to the five different time horizons on which the model is estimated, as described above;
- "Loan Age" refers to the age of a loan in months in a given period, updated dynamically in each projection quarter. The loan age segments are outlined in the "Variable Description" column;
- "Origination Risk Score" refers to the credit score of a borrower at the time of loan origination, divided into segments outlined in the "Variable Description" column;
- "Joint Application" is a flag for whether a loan has a joint application. The variable is assigned a value of one if the loan has a joint application (multiple co-borrowers), and is assigned a value of zero otherwise;
- "Seasonality" is a flag for whether an observation occurred in the first half of the calendar year. The variable is assigned a value of one in the first half of the calendar year, and is assigned a value of zero otherwise;
- "Delinquent" refers to the level of delinquency of a loan, among delinquent loans. The categories are defined based on number of days past due (DPD);
- "Ever30" is assigned a value of one if a current loan has previously been more than 30 days past due ("DPD") over the previous year;
- "UR" is the level of unemployment rate in the borrower's state of residence;
- "YoY change" refers to year-over-year change in the state unemployment rate and year-over-year percent change in the state house price index ("HPI"), for a given Variable Description. Unemployment rate change is interacted[509] with the 661-720 and 720+ risk score categories to allow the impact of unemployment rate change to vary based on borrower characteristics.

(2) Support for Model Decisions

The design and specification of the Auto PD Model is supported by a review of the relevant literature and industry best practices, statistical fit, and modeler expert judgment. This section describes both the support for the overall model design as well as the specific variables and transformations included in the model.

Support for Model Design

The Auto PD Model uses a hazard model to project the path of default rates over the stress test horizon. A hazard model is a type of model that projects the probability of an event (in this case default) occurring at a certain point (in this case, in each period), given that the event

[509] "Interacted with" in this context means that the impact of a change in unemployment rate is allowed to vary based on the original credit score of a borrower.

has not occurred in any previous period. This model structure is appropriate for use in a stress testing context, since the Auto Model is used to project the quarterly path of auto losses and allowances. For further discussion of the hazard model and comparison with other potential model structures, see Section F.ii.a.(4).

Support for Variables and Transformations Included in the Model

The Auto PD Model includes loan, borrower, and macroeconomic characteristics that account for the risk factors deemed by the Board to be the most important predictors of default risk in the portfolio, subject to data availability constraints. To determine these factors, the Board reviewed available data as well as other sources to consider a large number of variables that are potentially relevant to determining whether an auto loan will default. These other sources include academic literature, industry publications, and through the Board's supervision of the Large Institution Supervision Coordinating Committee ("LISCC")[510] and Large and Foreign Banking Organization ("LFBO")[511] portfolios. The choice of the covariates used in the model are informed by these sources and confirmed independently using statistical techniques. Most notably, when a certain variable enters the model with a statistically significant and economically meaningful coefficient, or notably improves the predictive accuracy of the model

[510] The Large Institution Supervision Coordinating Committee Supervisory is a program established by the Board to coordinate the Federal Reserve's supervision of large financial institutions that pose the greatest risk to U.S. financial stability. Financial institutions subject to the LISCC supervisory program include: (i) any firm subject to Category I standards under the Board's tailoring framework, (ii) any non-commercial, non-insurance savings and loan holding company that would be identified for Category I standards if it were a bank holding company, and (iii) any nonbank financial institutions designated as systemically important by the Financial Stability Oversight Council (FSOC). *See* "Large Institution Supervision Coordinating Committee," Board of Governors of the Federal Reserve System, https://www.federalreserve.gov/supervisionreg/large-institution-supervision.htm. *See also* "Large Financial Institutions," Board of Governors of the Federal Reserve System, https://www.federalreserve.gov/supervisionreg/large-financial-institutions.htm.

[511] The Large and Foreign Banking Organizing Organization Supervisory Program supervises all other large financial institutions (defined as U.S. firms with assets of $100 billion or more and foreign banking organizations with combined U.S. assets of $100 billion or more) that are not included in the LISCC program. *See* "Large Financial Institutions," Board of Governors of the Federal Reserve System, https://www.federalreserve.gov/supervisionreg/large-financial-institutions.htm.

with respect to a certain population of loans, this provides strong support for including that variable in the model. Conversely, when a variable enters an equation with an insignificant or counterintuitive sign, this suggests that either the effect of the variable is less important than expected, or that there are confounding factors that mitigate the impact of the variable. In these cases, the Board will review the data to assess the reason for this lack of impact to determine if a different specification (for instance, a transformation of the variable) would better capture the underlying economic relationship; if no such specification results in a statistically or economically meaningful impact, the variable is not included.

The above paragraph defines the principles used for determining the appropriate variables to include in the model. The rest of this section describes the variables that are included based on the results of this variable selection process; explanations rely on the estimated coefficients shown in Table F1 to support the interpretation of included variables.

First, the Board uses indicators for the elapsed time from the start of the projection (performance periods). The coefficients on these variables in the current equation indicate that loans that are current at the start of the projection horizon are relatively unlikely to default in the first six months, and considerably more likely to default afterwards. This is consistent with expectations, as it takes time for loans to progress from current to default. For loans that start as delinquent, the reverse is true: the estimated coefficients show that delinquent loans are more likely to default in the first six months compared to later periods. This is consistent with expectations as well, as if the loan does not default in the first six months, this means it has survived the acute delinquency and is therefore less likely to default going forward.

Borrower quality is assessed using an indicator for joint ownership and the origination credit score. Joint ownership generally reduces the riskiness of a loan, as the lender can rely on multiple borrowers to repay the debt; the variable enters the model with a negative sign, as expected.[512] Meanwhile, credit score is a widely used variable to assess the default risk of a borrower. Origination credit score is used, rather than a refreshed credit score, to align with the way data are reported on FR Y-14Q, Schedule A.2 (U.S. Auto Loan), as refreshed credit scores are not reported on this FR Y-14Q schedule.[513] The model is estimated by categorizing credit scores into one of five categories as shown in the model specification, defined as follows:

1. Deep subprime (Origination Credit Score <=560)
2. Subprime (Origination Credit Score >560 and <=620)
3. Near Subprime (Origination Credit Score >620 and <=660)
4. Near Prime (Origination Credit Score >660 and <=720)
5. Prime (Origination Credit Score >720)

These categorizations are defined in the instructions for FR Y-14Q, Schedule A.2 (Field A.4). Other sources, such as the Consumer Financial Protection Bureau (CFPB), also define credit scores into categories.[514] The CFPB's categories are similar to the above categories, except that "Deep subprime" is defined as credit scores below 580. While the cut-off point is slightly different, both definitions reflect the importance of accounting for different risk associated with borrowers with very low credit scores.

When using the model to project loss rates, these credit score coefficients are applied to corresponding categories on FR Y-14Q, Schedule A.2 (U.S. Auto Loan), Field A.4 ("Original commercially available credit bureau score or equivalent").

[512] In the FR Y-14Q data used to project losses, joint accounts are not separated from other accounts; instead, the share of balance on joint accounts within a segment is reported. The Board projects losses by running the equations for both joint accounts and non-joint accounts, and then weighting the results by the share of balance within a segment from accounts originated with a co-applicant.
[513] The Board stopped collecting refreshed credit score on the FR Y-14Q due to challenges getting complete reported data without overly burdening reporting firms.
[514] *See* "Borrower Risk Profiles," Consumer Financial Protection Bureau, https://www.consumerfinance.gov/data-research/consumer-credit-trends/student-loans/borrower-risk-profiles/.

Loan quality is assessed using real-time delinquency status, historical delinquency status, and loan age. As previously discussed, separate equations are used to project losses that are current at the start of the projection period compared to loans that are delinquent. Within the delinquent equation, loans are categorized based on the severity of the delinquency (30-59 days past due, 60-89 days past due, and 90-119 days past due),[515] with more severe delinquencies corresponding to higher default risk. In addition, the current equation includes whether the loan had a previous delinquency at any point in the previous 12 months; among current loans, those with a history of delinquency are substantially more likely to default.[516] Lastly, loan age in the performance period is included to account for the impact of seasoning. Empirical analysis shows that loans tend to be less likely to default as more time passes from origination. The instructions for FR Y-14Q, Schedule A.2 (U.S. Auto), field A.2 ("Age") segment loans into loan age categories spanning yearlong periods (less than one year old, 1-2 years old, etc.) to account for differences in seasoning while minimizing firm reporting burden. The specification used in the model follows that defined in the FR Y-14Q instructions.

Macroeconomic variables account for the increased rate at which loans default during periods of economic stress. Considering macroeconomic factors is particularly important for a model that is being used in the stress test, as the stress test models are used to project auto losses during a hypothetical recession. Since auto loans are a form of household credit, their performance is sensitive to household financial conditions. The Auto Model uses two variables,

[515] In all cases, loans that are subject to bankruptcy or repossession are considered defaulted rather than delinquent.
[516] In the FR Y-14Q data used to project losses, loans with previous delinquencies are not separated from other accounts; instead, the share of balance that at any given time in the previous 12 months had been 30 or more days past due is reported. The Board projects losses by running the equations for both previously delinquent and non-previous delinquent accounts and then weighting the results by the share of balance within a segment that is reported to have been 30 or more days past due in the previous 12 months.

the unemployment rate and the house price index, to represent these conditions, as described in detail below.

The Board uses unemployment rates to proxy for broad economic stress and households' ability to pay bills, based on academic literature on credit risk, industry best practices, and the Board's experience and expertise. Unemployment rates are broadly used in this context because they provide a comprehensive measure of the economic health of households and businesses. Higher unemployment rates can be an indication of stress on household budget constraints. These situations can lead households to default on their loans. The importance of unemployment rate is observed in academic literature across different retail loan products, including first lien mortgages (*see*, *e.g.*, Elul, Souleles, et al., 2010); home equity lines of credit (Hale, Krainer, and McCarthy, 2020); and credit cards (see, for example, Agarwal and Liu, 2003; and Belotti and Crook, 2013).

Meanwhile, home prices are a measure of borrower wealth; as home prices decline, so does household wealth, reducing the ability of borrowers to repay their loans. The Board uses both unemployment rate from the Bureau of Labor Statistics and an index of house prices from a third-party vendor in the model to capture a broad range of economic conditions.

Both unemployment rate and house price index enter the model at the state level.[517] Unemployment rate enters in two transformations. The level of unemployment accounts for the current state of the job market, while the year-over-year change in the unemployment rate accounts for recent deterioration in the job market, which can explain the prevalence of unexpected income shocks. In the current equation, the coefficient on the year-over-year change

[517] As described further below in this sub-section, The instructions for FR Y-14Q, Schedule A.2 (U.S. Auto) group states into six regions, designated in the instructions. When applying the coefficients to project PD, macroeconomic data are aggregated from the state level to regional level using historical auto loan balance (as calculated from the Credit Bureau Data) as weights. The exact weights are shown in Appendix 1.

in unemployment rate is allowed to vary by credit score bucket; in particular, it is empirically more impactful (as assessed based on the positive coefficients associated with these terms in Table F1) for borrowers in the near prime (risk score 661-720) and prime (risk score >720) buckets; including this interaction accounts for this empirical fact and ensures appropriate model sensitivity to unemployment rate across loans to borrowers in different segments. The result that prime borrowers have higher sensitivity to macroeconomic environment changes is consistent with academic literature on other retail credit products; see, for instance, Canals-Cerdá and Kerr (2015).[518] The house price index enters the current equation[519] as the year-over-year change to proxy for changes in household wealth; the negative coefficient on HPI in the equations demonstrate that increases in HPI are associated with lower default risk, while decreases in HPI are associated with higher default risk.

The paragraph above describes the treatment of macroeconomic variables when estimating the model parameters. However, the instructions for FR Y-14Q, Schedule A.2 (U.S. Auto) group states into six regions, designated in the instructions, rather than reporting every state separately. Therefore, when applying the coefficients to project PD, macroeconomic data are aggregated from the state level to regional level using historical auto loan balance (as calculated from the Credit Bureau Data) as weights. The exact weights are shown in Table F2.

Table F2 - Weights used to aggregate state-level macroeconomic variables to regions

State	Region	Weight
AZ	1	0.1060
CA	1	0.5136
FL	1	0.3369

[518] Canals-Cerdá, Jose J. and Sougata Kerr. 2015. "Credit Risk Modeling in Segmented Portfolios: An Application to Credit Cards," Working Paper 15-08 Federal Reserve Bank of Philadelphia.
[519] House price index changes are less relevant for loans that have already become delinquent, so this variable is not included in the delinquent equation.

State	Region	Weight
NV	1	0.0435
GA	2	0.1453
IL	2	0.1832
IN	2	0.1086
KY	2	0.0670
MI	2	0.1535
OH	2	0.1980
OR	2	0.0572
RI	2	0.0135
SC	2	0.0739
AL	3	0.0756
CT	3	0.0482
DC	3	0.0050
ID	3	0.0251
MO	3	0.0952
MS	3	0.0431
NC	3	0.1556
NJ	3	0.1226
PA	3	0.2008
TN	3	0.0993
WA	3	0.0967
WV	3	0.0330
CO	4	0.0903
DE	4	0.0171
MA	4	0.0956
NM	4	0.0392
NY	4	0.2651
TX	4	0.4927
AK	5	0.0144
AR	5	0.0619
HI	5	0.0176
IA	5	0.0666
KS	5	0.0558
LA	5	0.0934
MD	5	0.1212
ME	5	0.0315
MN	5	0.0964
MT	5	0.0190
OK	5	0.0851
UT	5	0.0595

State	Region	Weight
VA	5	0.1685
WI	5	0.0946
WY	5	0.0148
ND	6	0.1082
NE	6	0.3138
NH	6	0.2877
SD	6	0.1565
VT	6	0.1338

Finally, the model accounts for seasonality in default rates. Since the model is estimated semi-annually, only two periods are observed for each calendar year, corresponding to the first half and the second half of the year. The model accounts for the potential for seasonality by using an indicator variable to allow the model to reflect the historical observed seasonality. Historically, default risk is higher in the second half of the calendar year; this is reflected in that the coefficient on the variable for loans in the first half of the calendar year has a negative sign.

(3) Adjustments and Data Cleaning Steps

The Board makes several adjustments to ensure the estimation of the model is based on representative data and is minimally impacted by errors or outliers. These adjustments are described in detail in this section.

Estimation Sampling and Loan Inclusion

The Auto PD Model uses a 10 percent random sample of the non-defaulted auto loans reported in the Credit Bureau Data with non-zero balance. Data used in the Auto PD Model cover the period spanning from 2000 through 2019.[520] Each year of data includes two snapshots, corresponding to June and December. A semi-annual structure is used due to data availability. Additionally, the following loans are excluded to ensure the sample is representative of the population of loans reported on FR Y-14Q, Schedule A.2 (U.S. Auto Loan):

[520] *See* Section F.iii.a.(3) for further discussion on the impacts of excluding more recent periods of data from the model estimation sample.

- Loans with a balance of $0
- Loans from outside the 50 U.S. states and Washington, DC. Loans to international borrowers and borrowers in U.S. territories make up an immaterial share of firm portfolios, and are not modeled by the Auto Model in the supervisory stress test.[521]
- Loans with narrative codes that are associated with RVs, residential mortgages, home equity lines of credit, or credit cards[522]
- Loans with missing origination credit score[523]

Estimation Data Cleaning and Preparation

The Board's method for preparing the dataset for estimation of the model is informed by the Board's supervisory experience and expertise. To assess data quality, in line with established model development standards, the Board reviews descriptive statistics of each of the fields to determine which variables or observations must be cleaned or removed. In this section, certain data cleaning steps to prepare the data for estimation of the model are described.

First, individual loans are tracked over time. Loans are identified across time based on the consumer and loan origination month. While other features—such as original balance—can be used to further identify individual loans, in practice, the original balance field can be imprecise and relying on this field could cause observations of the same loan to be mischaracterized as different loans. In rare cases (less than 2 percent of loans) where these variables are insufficient to uniquely identify a loan, for instance, when in a single period, multiple auto loans are reported for the same borrower with the same origination month, the Board keeps only one loan in each period among those identified based on the criteria in the previous sentence. In particular, the Board uses the loan among those identified with the highest

[521] Losses on foreign auto loans and leases are projected in a separate model. *See* Section G for more details about the projection of losses for foreign auto loans and leases.
[522] Losses on these types of products are modeled by other retail models rather than the U.S. Auto Model.
[523] When the model is used to project losses, loans reported on the FR Y-14Q as having missing credit score are treated as deep subprime loans (FICO® <=560 or equivalent). *See* "Projection Data Cleaning and Preparation" for more details.

original balance; if there are still duplicates, the loan with the highest current balance is used; if there are still duplicates, the loan with the weaker (more delinquent) status is used; finally, if there are still duplicates, loans are chosen based on the account holder status (authorized user, individual, joint, etc.). This treatment is aligned with the stress testing principles of simplicity (reducing the complexity of tracking loans) and conservatism (using the more delinquent loan in certain cases) from the Stress Testing Policy Statement. For each period a loan is observed, the model links the loan with its payment status in up to five future semi-annual periods,[524] to identify whether the loan defaulted in the future. Contemporaneous macroeconomic variables, as outlined above in Section F.ii.a.(1), are assigned as well, based on the time period and borrower state of residence.

Next, certain observations in the data have missing values in the balance or payment status fields. Since these are critical fields for modeling, the Board imputes these values using the next available observation of that loan, when possible. If the next available observation cannot provide this information, these fields are left missing, and the associated observations are dropped.

With the payment status cleaned, it is used along with other variables to identify default. Loans are treated as defaulted if they trigger default conditions[525] in any of the months in the succeeding six-month period, regardless of the status at the period end. The data cleaning process also accounts for the fact that loans sometimes drop out of the sample, and that those missing loans are disproportionately those that were previously delinquent. The Board has assessed that loans that drop out of the sample often do so because they default and therefore stop being reported. If these missing loans were not accounted for, this could lead to

[524] Five future periods aligns with the number of periods over which the PD model is projected.
[525] As described in Section F.ii.a.(1).

underestimation of the default rate. Therefore, in situations where a loan exits the sample, the model imputes the next period's payment status based on other features of the data, using the following logic:

- If a period's status is unobserved and the loan's last observed balance is below the lower of 10 percent of the origination amount or $5,000, then the loan is assumed not to have defaulted. Loans where over 90 percent of the balance is paid off and a small amount of balance remains have accumulated significant equity on the vehicle and are thus unlikely to default.
- Otherwise, if a period's status is unobserved and the data shows that the borrower's worst status for all auto accounts reported to the data vendor in the previous three months met the default criteria, the loan is treated as defaulted in that quarter. In this case it is assumed that the borrower's worst status is reflective of this loan.
- Otherwise, if a period's status is unobserved, the borrower's worst status for all auto accounts reported to the data vendor in the previous three months is unknown, and the borrower's most recent credit score is below 540, then the loan is treated as defaulted in that quarter. Credit scores this low could be indicative of a recent charge-off event, especially considering the missing data. In line with the stress testing principle of conservatism, the Board assumes that this behavior is associated with a recent default.

Finally macroeconomic data is merged in, based on the U.S. state of the loan.[526] The macroeconomic variables used in the model are described below:

- House price index, sourced from a third-party vendor.
- Quarterly average of the seasonally adjusted unemployment rate, produced by the Bureau of Labor Statistics.

Considerations on Data Representativeness

Since the model is used to project losses on the auto loan portfolios of institutions subject to the stress test, it is important to consider whether the data used to estimate the model is representative of the data for which the model is projecting losses. For instance, if the sample of loans used to estimate the model is more or less risky than the loans for which the model is

[526] *See* Section III.B of the Enhanced Transparency and Public Accountability Proposal for more information on the processes used to create these historical datasets, including seasonal adjustments.

projecting losses—across characteristics that are either unobservable or not included in the model —this could lead to inappropriately low or high loss projections in the stress test.

The Auto PD Model accounts for this by incorporating the variables deemed by the Board to be the most important factors associated with auto loan default risk into the PD model; however, due to data limitations and unobservable factors, representativeness may still be a concern. In particular, the Board does not account for whether the lender was a covered firm when calibrating the Auto Loan model parameters, as the lender cannot be observed in the Credit Bureau Data. However, while short-term loss rate back-testing analysis using the FR Y-14Q data suggests that covered firms may be less risky than other auto lenders in benign periods, especially for non-prime loans, the model fits well when applied to data from the 2008 financial crisis period. In line with the stress testing focus on the ability to evaluate the impact of severe economic stress from the Stress Testing Policy Statement, the Board determined it remains reasonable to use the model calibrated using industrywide data in spite of evidence of over-prediction during benign periods. However, the Board will continue to monitor the performance of the model to identify any changes to the Board's determinations surrounding concerns over representativeness.

Projection Data Cleaning and Preparation

The format of the FR Y-14Q U.S. Auto data has certain formatting and stylistic differences from the Credit Bureau Data, requiring certain data cleaning steps to allow the model to be used for projection.

First, while the model is estimated using loan-level data, the FR Y-14Q is reported at the segment level. For each segment,[527] certain summary statistics are reported. These summary

[527] A full list of variables used to segment the data can be found in the FR Y-14Q instructions.

statistics include dollars outstanding, number of accounts, net dollars charged off, and many other variables used in the model. To apply the Auto PD Model to the segment-level data, each segment is effectively treated as a series of loans with identical characteristics.[528] For variables—such as credit score, delinquency status, and loan age—that are included in the segmentation, the coefficient on the associated segment is applied; for other variables that are reported as summary statistics—including the share of accounts that have been delinquent in the past year and the share of joint accounts—the model is run for each plausible value of the variable, and the PD projection is then weighted by the reported shares.[529]

Similarly, while state-level house price index and unemployment rate are used in estimation, states are aggregated into six regions on FR Y-14Q, Schedule A.2 (U.S. Auto), to minimize the burden to firms of reporting this schedule. In projection, state-level macroeconomic data from the Stress Test Scenarios are aggregated into regions by weighting the state-level values by the historical share of auto balances in the region that are attributable to each state, expressed in Table F2.[530]

[528] Only new and used auto loans are included. Auto leases are removed from the data prior to projection.
[529] In particular, the model equations are run four times, corresponding to each of (1) not a joint account, not previously delinquent; (2) not a joint account, previously delinquent; (3) joint account, not previously delinquent; (4) joint account, previously delinquent. Each of these four runs produces a probability of default for the segment. These four probabilities are then weighted by the shares of the segment in each of these four categories to produce a weighted probability of default for the segment. To avoid unreasonable impacts caused by missing or erroneous input data, these shares are bounded at 0 percent and 100 percent**.** This choice is reasonable as long as the correlation between the likelihood of an account being joint and the account being delinquent is low. The Board regularly performs a test to check this correlation, which is about one percent historically. Based on these results the Board has assessed that this treatment is reasonable.
[530] Consistent with other loan loss models, the stress test assumes that there is no geographic variation in the path of the scenarios across states. However, the exact state-level paths can vary based on differences in historical and starting-point values. *See* Section III.B in the Enhanced Transparency and Public Accountability Proposal for more information. Additionally, because the Auto PD Model is semi-annual, and 13 quarters of projections are needed to produce estimates of provisions, the model uses 14 quarters of scenario data. The projections of unemployment rate and house price index for the 14th projection quarter, which are not in the Stress Test Scenarios, require assumptions about the long-term path of these variables. For the purposes of creating projections of unemployment rate in the 14th projection quarter, the Board assumes that the unemployment rate will continue to converge toward the assumed natural (long-term) rate of unemployment following the end of the published scenario. For the purposes of creating projections of house price index in the 14th projection quarter, the Board assumes that house price index will continue to evolve such that the ratio of house price index to per capita disposable personal income will

The models also account for missing or misreported data on the FR Y-14Q. While firms are responsible for ensuring the completeness and accuracy of data reported in the FR Y-14 information collection, the Board makes efforts to validate firm-reported data and requests resubmissions of data where errors are identified. If data quality remains deficient after resubmission, the Board applies conservative assumptions to a particular portfolio or to specific data, depending on the severity of deficiencies, in line with the stress testing principle of conservatism. For categorical variables, such as credit score or loan age, the model assumes loans with missing data belong in the category with the highest loss projections. For continuous variables—such as the share of accounts that have been delinquent in the past year and the share of joint accounts—the model assigns the 10th or 90th percentile value, whichever is more conservative, based on data reported by all firms.[531] In the rare case that a firm's submitted data are too deficient to produce a supervisory loss estimate, the Board assigns a high loss rate to the portfolio balances based on supervisory projections of auto losses for other firms. This high loss rate is based on the loss rate path of the 90th percentile firm ordered by loss rates, with the percentiles calculated based on 13-quarter losses. In the case where no firm is exactly at the 90th percentile, the loss rate path of the firm immediately after the 90th percentile is used.

Next, the loan age variable must be adjusted each period to account for loan aging through the projection period. Since the FR Y-14Q segments loans by age, and the age segments categories each encompass a full year, an assumption must be made about the exact age of loans in each segment to roll the age forward by six months per projection period. The model accounts for this by assuming all loans in an age category are 5.5 months older than the lower bound of

continue to converge to its long-term historical average (excluding extreme values from prior to and during the 2008 financial crisis period) following the end of the published scenario, and that disposable personal income will continue to evolve such that it reaches a constant share of projected GDP.

[531] In this calculation, segment-level data are weighted by the number of accounts reported in a given segment.

the age bucket at the start of the projection period. This assumption is consistent with the stress testing principle of conservatism, as given uncertain data, it assumes that loans are less seasoned and therefore will take longer to reach the seasoned categories that are treated as less risky by the model. Analysis conducted by the Board using the Credit Bureau Data, which allows identification of loan age in months, confirms that this treatment is reasonable.

A final consideration for projection of the Auto PD Model is that while the model is only estimated over five performance periods, corresponding to the second, fourth, sixth, eighth, and tenth projection quarters, the model is used to project losses over 13 projection quarters, for computation of allowances. Later performance quarters were not included in the model due to the small number of defaults observed in the data after 10 quarters;[532] given the short duration of auto loans, very few loans that remain active for 10 quarters proceed to default after that period, as many borrowers have paid off the loan by this point and those who have not have seasoned loans that historically default very rarely. To allow projection of the full 13-quarter loss path, the model is projected for 14 quarters, and the coefficient on the 10th-quarter performance period is applied to the final two semi-annual projection periods. This allows the model to rely on stable coefficient estimates in projecting loss rates throughout the projection horizon. In the current equation, the impact of this assumption is minimal, as the performance period coefficients covering these periods would be approximately equivalent to the 10th-quarter coefficient. In the delinquent equation, this assumption is slightly conservative, as including more performance periods would lead to lower coefficients on later performance periods; however, given that Board

[532] A review of the estimated coefficients in the PD model suggests that the small number of observed defaults after 10 quarters is not directly due to the number of elapsed quarters of the projection but rather due to the effects of seasoning; by the end of the 10th quarter, all observed loans have sufficiently high loan ages to be less risky going forward (as shown by the lower coefficients on higher loan age categories in Table F1). The model accounts for the fact that loan age will continue to increase after 10 quarters; as a result, the Board assessed that the model sufficiently accounts for reasons why defaults are observed rarely after 10 projection quarters.

analysis of the historical data shows that few delinquent loans remain in the data after the 10th projection quarter, the Board believes this conservative assumption to be reasonable, and unlikely to materially impact results.

(4) Alternatives

Alternative Model Structures

The Auto PD Model uses a loan-level, multi-period, discrete-time hazard approach, which projects the likelihood that a loan will default in each period, given that it has not defaulted already. This approach is valuable in the context of the stress test, which requires the projection of auto loan loss rates over the course of a hypothetical scenario.

The public domain includes numerous examples of hazard models, as well as other types of models, for modeling credit events.[533] While the majority of academic work focuses on other portfolios—such as residential mortgages and corporate lending—the principles are applicable to other areas of consumer finance, including auto lending. The Board considered a wide range of approaches in determining the appropriate model.

The Board's decision to use a loan-level model is intended to increase the interpretability of the model results. Further, relative to other alternative approaches, the Board assesses this approach as most consistent with modeling best practices and best suited for use in the context of the supervisory stress test. The Board also considered using a design that would project default rates for different segments, rather than at the loan level. In particular, rather than tracking whether an individual loan defaults over time, a segment-level approach would track the share of loans in a given segment that defaulted in each period. This segment-level model has the advantage of a data structure that is more similar to the structure of the FR Y-14Q, requiring less

[533] *See*, *e.g.*, Calem and Lacour-Little (2002); and An et al (2010). Calem, Paul S. and LaCour-Little, Michael, 2002, Risk Based Capital Requirements for Mortgage Loans.

data cleaning. Additionally, segment-level models can produce high levels of in-sample fit. However, a segment-level model does not rely on data as granular as a loan-level model, creating challenges of its own. Ultimately, the Board determined that the limitations of a segment-level approach outweigh the benefits. First, the segment-level model structure does not easily allow for the inclusion of certain important variables, such as previous delinquency status of a given loan, constraining the modeling options available when it is used. Second, an alternative, segment-level model developed by the Board was shown to have coefficients with counterintuitive signs[534] on key variables. These counterintuitive signs raise concerns that despite strong in-sample fit, out-of-sample performance may be weaker, as these spurious relationships may not retain their explanatory power in future economic environments. Due to these considerations, the Board chose the loan-level model.

The determination to use a multi-period model, as opposed to a single-period model, is necessitated by the design of the stress test. The stress test uses quarterly loss estimates to produce projections of the balance sheets of covered institutions over a nine-quarter horizon. This substantially limits the utility of model structures that produce a single estimate of losses, rather than a path. The chosen multi-period hazard approach provides semi-annual projections[535] of default rates, allowing projections of not just the total default rate but its shape.

Using finer periods, such as quarters, was also considered but ultimately not chosen due to data availability constraints. While the Board has access to quarterly, account-level data on auto loans in recent years, the data are not available at a quarterly frequency during any period of

[534] Counterintuitive signs occur when a variable is expected to have a certain relationship with default, but the estimated equation shows the opposite effect. For instance, economic theory suggests that higher unemployment rates would be associated with higher default rates. If a model specification includes a negative sign on unemployment rate in an equation (indicating that higher unemployment rate is associated with lower probability of default), this would be considered counterintuitive and require further investigation.

[535] Conversion of the semi-annual projections to quarterly projections is further discussed in Section F.ii.d.

significant stress in the auto market, such as the 2008 financial crisis period. Other datasets, such as the FR Y-14Q, which is reported at a quarterly frequency back to 2007, were also considered; however, the segment-level data reported in this dataset constrains the available modeling approaches and would not allow the estimation of a loan-level hazard model as the Credit Bureau Data does. Given these constraints, estimating using a semi-annual frequency allows the model to account for the path of the default rate over the course of the forecast horizon while producing accurate, risk-sensitive projections. Simple imputations are used to produce reasonable loss estimates in odd quarters of the projection horizon.

Additionally, only one outcome variable, default, is considered. As a result, other competing outcomes, such as prepayment, do not enter the model. This choice simplifies the modeling framework as it does not require the development of additional specifications to account for prepayment. Instead, as will be described in Section F.ii.d, paydown rates are assumed to be stable. Including prepayment directly in the model would allow it to account for certain situations that would lead to especially high or low prepayment. These could indirectly impact PD, as loans that prepay by construction cannot default. However, the simplicity of the one-outcome approach outweighs the benefit. Due to the assumption of a constant balance sheet in the supervisory stress test, the potential impact is further mitigated. The constant balance sheet assumption mitigates the impact as the model assumes that paid-off balance is replaced with new origination balance. Therefore, given the assumptions of the supervisory stress test, the rate of prepayment does not in practice impact the balance of the portfolio to which the PD model is applied in each period.

Given these choices, the Board considered other model structures for projecting a multi-period, semi-annual model, in addition to a hazard model. One alternative to a hazard model is a state transition model (see, for instance, Chen et al. 2020),[536] under which loans are allowed to transition between payment status (for instance, current, delinquent, etc.) in each period. This approach allows for the tracking of the path of loan behavior over the course of the projection period and allows the loan characteristics to update dynamically through the period. While this approach allows for more detailed projections and allows the risk characteristics to vary based on these transitions, it would add substantial complexity to the model, reducing interpretability. A state transition model also requires a higher data frequency compared to the semi-annual frequency of Credit Bureau Data. This is because transition models rely on calculating the probability of loans transitioning from current to various intermediate delinquency stages to default. With a semi-annual data frequency, this entire process usually will occur within one period, reducing visibility into the transitions. Furthermore, dynamically projecting state changes makes it challenging to incorporate the past delinquency variables into the model, as these variables are probabilistic during the projection period. This is problematic as past delinquency is a key predictor of default for current loans. Given these constraints, and that the output of the model is intended to project stressed losses rather than the entire range of possible statuses, the hazard model is used rather than a state transition model.

Alternative Covariates

Given the choice of the loan-level, multi-period, hazard model, there are many possible variables and transformations of variables considered for inclusion into the model. The specification of the Auto Model is consistent with the factors outlined in the Stress Testing Policy Statement and informed by many considerations, including expert judgment and statistical fit.

[536] State transition models are used by many industry and government actors, such as HUD. See Annual Actuarial Review of the FHA Mutual Mortgage Insurance Fund Forward Loans – Fiscal Year 2024. United States Department of Housing and Urban Development, November 13, 2024, https://www.hud.gov/sites/dfiles/Housing/documents/2024-MMI-Forward-Loans-Final-Report.pdf.

The range of available covariates is limited by data availability constraints in both the Credit Bureau Data and the FR Y-14Q U.S. Auto segment-level data used to project loss rates. For instance, while the refreshed credit score may incorporate information relevant to predicting auto losses not included in the origination credit score, refreshed credit score is not available on the FR Y-14Q.[537] Similarly, while new car loans and used car loans likely have different default probabilities, the Credit Bureau Data does not account for whether a loan was for a new or used car, preventing its inclusion in the Auto PD Model. Also, the segmentation of certain variables on the FR Y-14Q, such as credit score and loan age, prevents differentiating the riskiness of loans within the categories. Finally, loan-to-value ratio is expected to impact default risk, as borrowers with less or no equity in their vehicles are generally more likely to default compared to borrowers with more equity. However, loan-to-value ratio is not included in the Credit Bureau Data, preventing its inclusion in the Auto PD Model.

Certain other variables were considered but not included in the model to align with stress testing principles of stability and robustness. For instance, while additional segmentation is available for loan age, compared to what is included in the model, the Board assessed, based on Board analysis of the Credit Bureau Data and the FR Y-14Q data, that defaults are unlikely once the loan age is greater than three years. Since including additional loan age categories could lead to spurious coefficients, all loans greater than three years old are treated the same by the model.

The inclusion of interest rate information was also considered. Domestic auto loans tend to be fixed rate products,[538] so shocks to market interest rates do not generally change loan terms

[537] Refreshed credit score was dropped from the FR Y-14Q to reduce the burden on firms reporting this schedule.
[538] Per the Consumer Financial Protection Bureau, "most auto loans are fixed rate" and "variable interest automobile loans are uncommon." See "Can I Negotiate a Car Loan Interest Rate with the Dealer?" Consumer Financial Protection Bureau, https://www.consumerfinance.gov/ask-cfpb/can-i-negotiate-the-interest-rate-on-an-auto-loan-with-the-dealer-en-795/#:~:text=Most%20auto%20loans%20are%20fixed%20rate%2C%20which,are%20looking%20for%20a%20consistent%20monthly%20payment.

for individual auto loans. However, they do impact interest rates of loans originated following the shock. This could potentially lead to changes in riskiness, as loans with higher interest rates will have higher monthly payments for a given loan size and term, potentially reducing borrower's ability to repay the loan. In addition, changes in interest rates may impact borrowers' debt service burden through other loan products or impact their access to new credit, which could in turn influence ability to repay auto loans. In recent years, as interest rates increased sharply, the Board assessed whether models were appropriately capturing risks due to the changing interest rate environment. Ultimately, internal analysis supported the Board's determination that the model's behavior is appropriate despite not accounting for interest rate changes. This internal analysis consisted of the following:

- A review of supervisory materials indicated that lenders account for increased payments by maintaining debt-to-income thresholds, either by limiting the size of the loan or by extending the term of the loan.
- The Board tested an alternative specification of the model directly including the imputed interest rate of the loan. Results from the alternative model indicated that the inclusion of interest rates would only provide modest amounts of predictive power, not justifying the increase in complexity. Furthermore, to the extent that the analysis showed that higher interest rates were associated with default, this effect might be due to higher interest rates proxying for less creditworthy borrowers rather than changes in the macroeconomic environment, as less creditworthy borrowers tend to pay higher interest rates to compensate lenders for the additional risk.

As additional information and research about the impact of interest rates on the auto lending environment become available, the Board will continue to monitor its importance and the appropriateness of not including measures of interest rates in the model.

In addition to interest rates, other alternative macroeconomic factors were considered. The Auto PD Model includes both levels and changes of unemployment as a measure of labor market strength, as well as change in house price index as a measure of household wealth. Other factors, such as GDP growth and real disposable personal income, were also considered but were unable to as effectively account for historical auto PD behavior.[539]

Finally, the Board also considered a simpler approach to inclusion of unemployment rate changes. While the Auto PD Model allows the sensitivity of default rates to unemployment rate changes to vary based on the credit score of the borrower, a simpler approach would be to assume that this sensitivity is consistent across all auto loans. However, the high coefficient in the Current Equation for prime borrowers demonstrates the importance of accounting for variation in the impact of unemployment rate changes on probability of default.[540] This finding justifies the decision to allow the relationship between unemployment rate changes and probability of default to vary for borrowers in different origination credit score categories. Without including this interaction term, the model may underpredict default rates for high credit score loans in an environment where unemployment rates are rapidly increasing.

(5) Questions

Question F1: Should the Board incorporate interest rates into the Auto PD Model equations? If so, how could the Board ensure that this variable would be properly capturing the macroeconomic environment where higher interest rates cause payment difficulties, rather than proxying for borrower quality?

Question F2: The model coefficients are calibrated using industrywide data on auto loan performance, which might not be representative of the loans reported by firms on FR Y-14Q,

539 Including too many macroeconomic variables (for instance, both unemployment rate and disposable personal income) is problematic due to the collinearity of many macroeconomic indicators. The inclusion of variables with similar historical path risks producing spurious or counterintuitive coefficients for the individual variables.

540 As noted previously, this is consistent with research on other forms of retail credit. *See*, *e.g.*, Canals-Cerdá (2015).

Schedule A.2 (U.S. Auto Loan). Should the Board adjust the model assumptions to account for this representativeness concern? If so, how should the model assumptions be adjusted?

b. Loss Given Default Model

(1) Description

The Board models the LGD for auto loans as a function of loan as well as borrower characteristics and macroeconomic variables. The historical data used to estimate this model are segment-level data provided by the firms on FR Y-14Q, Schedule A.2 (U.S. Auto Loan), covering the period starting in the first quarter of 2007[541] and ending in the last quarter of 2019.[542] The model estimates the LGD for defaulted loans within a segment using a linear regression model as shown in Equation F2. The model then projects LGD by applying coefficient estimates to segment-level data from the FR Y-14Q.

Specifically, this model is estimated using weighted least squares. Weighted least squares is a form of a linear regression model where observations are weighted to allow certain observations to be given additional importance in setting model parameters. In this case, weights are set based on the total unpaid principal balance at charge-off across all loans that charged off in the segment in the period, as reported in FR Y-14Q, Schedule A.2 (U.S. Auto Loan), Field B.32.

For modeling purposes of the supervisory stress test, the LGD in quarter t is defined as the total net dollars charged off in quarter t, as defined on FR Y-14Q, Schedule A.2 (U.S. Auto), Field B.14, divided by the total unpaid principal balance amount at charge-off for loans charged-off in quarter t, as defined on FR Y-14Q, Schedule A.2 (U.S. Auto), Field B.32.

[541] The first quarter of 2007 corresponds to the first period for which historical FR Y-14Q data are available.
[542] A discussion of the choice of the estimation sample period is available in Section F.iii.a.(3).

The segmentation in the LGD model is driven by the characteristics most associated with loss severity; in particular, product type (used vs. new vehicle), origination LTV, segment loan age, and origination credit score.

Macroeconomic variables account for changes in loss severity based on the macroeconomic environment. The LGD model uses year-over-year changes in a used vehicle price index obtained from a vendor, year-over-year changes in the state house price index, [543] and year-over-year changes in the national unemployment rate. Variables accounting for seasonality are also included, reflecting that used car values are generally higher in the spring and decline over the rest of the calendar year.[544]

The full specification is available in Table F3.

[543] As with the model projections in the PD model, since the FR Y-14Q aggregates state-level portfolio data into six regions, state-level house price index aggregated to regional macroeconomic variables based on the historic distribution of auto loan balance in the Credit Bureau Data attributable to each state within a region. In the case of the LGD model, these weights are used both when estimating the model coefficients and when using the coefficients to project losses, as both processes rely on the FR Y-14Q data. The specific weights are available in Table F2.
[544] The effects of seasonality on auto used prices are detailed in F.ii.b.(2).

Table F3 - LGD Model Specification

Parameter	Variable Description	Estimate	Standard Error
Intercept		0.4906	0.0014
Product Type	New Vehicle	-0.0527	0.0006
	Used Vehicle	--	--
Loan Age	Less than 1 yr	0.1038	0.0011
	Between 1 and 2 yrs	0.0466	0.0010
	Between 2 and 3 yrs	0.0320	0.0010
	Between 3 and 4 yrs	0.0103	0.0011
	Greater than 4 yrs	--	
Origination LTV	Missing	0.2301	0.0077
	<=90	-0.1063	0.0012
	91-120	-0.0605	0.0006
	>120	--	--
Origination Risk Score	Missing	0.1000	0.0020
	<=620	0.0791	0.0011
	621-660	0.0313	0.0012
	661-720	0.0215	0.0012
	720+	--	--
Performance Quarter	1	-0.0440	0.0008
	2	-0.0893	0.0008
	3	-0.0247	0.0008
	4	--	--
YoY Change	Unemployment Rate-US	0.0168	0.0003
	HPI - Region	-0.0016	0.0001
	Used Vehicle Price Index - US	-0.0021	0.0001

Where the parameters are defined as follows:

- "Intercept" refers to the intercept of the regression equation;
- "Product type" refers to the loan product (used or new vehicle). This is drawn from FR Y-14Q, Schedule A.2 (U.S. Auto Loan), Field A.1 (Product type).[545]
- "Loan Age" refers to the age of a loan in months in a given period, updated dynamically in each projection quarter. These categories are drawn from FR Y-14Q, Schedule A.2 (U.S. Auto Loan), Field A.2 (Age). The loan age segments are outlined in the "Variable Description" column;
- "Origination LTV" refers to the loan-to-value ratio of a loan at the time of loan origination, drawn from FR Y-14Q, Schedule A.2 (U.S. Auto Loan), Field A.3 (Original LTV) and divided into segments outlined in the "Variable Description" column;
- "Origination Risk Score" refers to the FICO® Score or equivalent credit score of a loan at the time of loan origination, as reported on FR Y-14Q, Schedule A.2 (U.S. Auto Loan), Field A.4, divided into segments with cutoffs defined using FICO® Scores, outlined in the "Variable Description" column;

[545] Despite being an allowed value in this field, auto leases are not included in the LGD model, due to the small size of the auto lease portfolio. See Section F.iii.a.(1) for more information about the treatment of auto leases.

- “Performance Quarter” refers to the calendar quarter of an observation to account for seasonality;
- “YoY change” refers to year-over-year change or percent change in a given macroeconomic variable, for each variable in the “Variable Description” column. Macroeconomic variables include unemployment rate, house price index, and used vehicle price index. For unemployment rate, this is the difference between the unemployment rate and its value from the previous year; for the house price index and used vehicle price index, this is the percentage difference between the index value and the index value from the previous year.

(2) Support for Model Decisions

Support for Model Design

The Auto LGD Model relies on representative industry data reported on the FR Y-14Q to calculate loss severity. The weighted least squares approach allows for a simple implementation that provides consistent, interpretable estimates of LGD across firms. For further discussion of the model structure and possible alternatives, see Section F.ii.b.(4).

Support for Variables and Transformations Included in the Model

Similar to the Auto PD Model, the Auto LGD Model includes loan, borrower, and macroeconomic characteristics that account for the risk factors deemed by the Board to be the most important predictors of loss given default in the portfolio, subject to data availability constraints. To determine these factors, the Board uses available data as well as other sources to consider a large number of variables that are potentially relevant to determining the share of auto balance that will not be recoverable in the case of default. These other sources include academic literature, industry sources, and other data obtained through the Board’s supervision of the Large Institution Supervision Coordinating Committee (“LISCC”) and Large and Foreign Banking Organization (“LFBO”) portfolios. The choice of the covariates used in the model are informed by these sources and confirmed independently using statistical techniques, as described for the Auto PD Model in Section F.ii.a.(2).

In terms of portfolio quality, loans are segmented based on four variables: product type, loan age, loan-to-value ratio at origination, and credit score at origination. Generally, the segmentation follows the reporting in the FR Y-14Q; in certain cases, due to sparseness or lack of historical information, FR Y-14Q segments are combined.[546] The inclusion of product type reflects that used cars tend to have higher loss severity than new cars.[547] The inclusion of loan age reflects that depreciation is sharper early in a loan's history, while amortization of the loan causes balances to decline faster as the loan ages. As a result, less-seasoned loans have higher LGD than more seasoned loans. Loan-to-value at origination is included as well, to account for loans with more borrower equity (lower starting LTV) typically having higher recovery rates and loans with less borrower equity, or even negative equity at origination, tending to have smaller recoveries.[548] Finally, the inclusion of credit score reflects borrower credit quality; loans to borrowers with lower origination credit scores tend to have higher loss severity in the case of default, as evidenced by the larger coefficients in Table F3 for lower credit score categories.

Similar to the Auto PD Model, macroeconomic variables are included in the Auto LGD Model to account for the substantial differences in recoveries during different economic environments. The year-over-year change in the unemployment rate is included to account for labor market strength, with larger increases reducing the ability of borrowers in distress to repay their loans. The year-over-year percent change in house price index is an indicator to proxy for household wealth. The negative coefficient on house price index in the model (shown in Table

[546] For instance, loans greater than four years old are combined, and the lowest two credit score segments are combined.

[547] The FR Y-14Q instructions include a third product type category, auto leases. However, auto leases are reported sparsely and are excluded from projections; therefore, they are removed from the estimation sample.

[548] The FR Y-14Q instructions previously required reporting of retail LTVs, before the instructions were updated to require reporting based on the wholesale price of the vehicle. While retail LTVs are generally lower than wholesale LTVs, the Federal Reserve determined that separating these categories did not meaningfully improve the statistical fit of the model. Therefore, the model treats all reported LTV values equally.

F3) demonstrates that the impacts of changes in household wealth are meaningful; in particular, increases in house price index lower LGD. This is likely due to the fact that increases in household wealth are associated with increased demand for vehicles and thus higher auto resale prices. The national unemployment rate enters the model; the house price index values rely on state-level input data. Since the FR Y-14Q aggregates state-level portfolio data into six regions, state-level house price index is aggregated to regional macroeconomic variables based on the historic distribution of auto loan balances attributable to each state within a region in the Credit Bureau Data. These weights are available in Table F2. Relying on regional measures of economic strength is advantageous in the Auto LGD Model, as the segments in the FR Y-14Q are defined based on housing market behavior during the 2008 financial crisis period. The incorporation of regional economic conditions allow the model to account for the fact that house prices fell by a higher percentage in certain regions compared to others during this period. Note that when applying the coefficients to produce projected LGDs, the model uses the projected values of these variables from the Stress Test Scenarios. When projecting values of house price index, the stress test assumes that there is no geographic variation in the path of the scenarios across states. However, the exact state-level paths can vary based on differences in historical and starting-point values. *See* Section III.B of the Enhanced Transparency and Public Accountability Proposal for more information.

In addition to house price index and unemployment rate, the Auto LGD Model also incorporates a direct measure of auto prices using an index of used vehicle prices produced by a third party. This variable enters the model through the year-over-year percent change in the index value. The intuition of including this variable is that an increase in vehicle prices is associated with higher recovery values, as the collateral value is higher, while a decrease is associated with lower recovery values. As expected, the coefficient on auto prices enters the model with a negative sign in Table F3. Reflecting that auto prices tend to move in sync across geographies,[549] values of the auto price index are projected at the national level during the projection period.

Finally, the quarter when the charge-off and recovery is reported is included, to account for seasonality of auto LGD. As used vehicle values tend to be highest in the spring,[550] LGD tends to be reduced in the second quarter and rises through the second half of the calendar year.

(3) Adjustments and Data Cleaning Steps

Several data cleaning steps are required to use the data reported on the FR Y-14Q to estimate the model. First, as institutions can enter and exit the panel over time, the estimation is based on a consistent sample of firms. Using a consistent sample of firms prevents the inclusion or exclusion of a firm from causing sharp changes in calculated historical LGD, which could lead to model estimates of certain variable coefficients that are not based on the underlying economic relationships. In the final specification, a panel of 12 reporting institutions is used, covering 70 percent of total balances and 90 percent of total net losses reported over the sample period. These 12 institutions include portfolios across the risk spectrum and are generally representative of the portfolios on which losses are projected in the stress test exercise.

For certain reporters in certain periods, charge-off information is unreliable. Since the unreliable data is associated with historical reporting and resubmissions were in many cases not

[549] Unlike residential real estate, vehicles are mobile and can be directed to areas with higher demand, limiting the regional variation in auto prices compared to house prices.

[550] *See*, *e.g.*, the Consumer Price Index for used cars and trucks, which generally has higher values in the first half of the year compared to the second half of the year. While this relationship was not observed in 2020 and 2021, this is likely due to the distortions in the used car market as a result of economic effects related to the COVID-19 pandemic. *See* U.S. Bureau of Labor Statistics. (n.d.). *Used Cars and Trucks in U.S. City Average, all urban consumers, not seasonally adjusted (CPI-U)* (Washington DC: United States Bureau of Labor Statistics), https://data.bls.gov/timeseries/CUUR0000SETA02?output_view=data.

feasible, in cases where the unpaid principal balance at charge off variable is unreliable, adjustments to the input data are made. In cases where feasible, unpaid principal balance at charge-off is estimated using the sum of gross contractual charge-offs and gross bankruptcy charge-offs reported during the period. To ensure this approximation is reasonable, the Board compared calculated gross charge-offs reported immediately before and after the end period of the unreliable data, and found that there was no visible "jump" in the data, indicating that this approximation is reasonable.[551] In certain other cases, where approximation does not remediate the underlying data issue, the problematic data are removed entirely from the estimation sample.

The FR Y-14Q data are reported monthly,[552] and must be aggregated to quarterly for use in the model. This step is performed by summing the variables that represent flows (for instance, net charge-offs) and averaging the variables that represent stocks (for instance, total balance).

As the FR Y-14Q field definitions change over time, the Board ensures the data are defined consistently across the panel. In particular, prior to a historic schedule revision, the FR Y-14Q instructions segmented by "vintage" instead of "loan age," where the vintages were based on calendar year. For observations reported under this version of the instructions, the loan age is assumed to be the number of years between origination year and current year for loans reported in the third or fourth quarter of the calendar year, and one fewer than the number of years between origination year and current year for loans reported in the first or second quarter of the calendar year.[553] This mapping is not exact in some cases; for instance, a loan observed in the third quarter of a year that is marked as having been originated in the previous calendar year will

[551] A visible "jump" would have indicated a change more likely driven by the different calculation used during the unreliable period than by a sudden change in gross charge-offs.
[552] Firms are required to report FR Y-14Q, Schedule A.2 (U.S. Auto Loan) each quarter. Each quarter of reporting separately includes data reported as of each of the three calendar months within the quarter.
[553] For loans reported as having been originated in the "current calendar year," loan age was assumed to be less than one year regardless of where in the calendar year the observation was reported.

be treated as between one and two years old, even if it was in fact originated in the fourth quarter of the previous year. Despite this imprecision, the mapping of "vintage" categories to "loan age" categories is on average correct and allows for the maximal inclusion of data while ensuring that the definitions align across different periods, as closely as possible.

Finally, the macroeconomic variables used in the model are merged in with the FR Y-14Q data. Similar to the Auto PD Model, historical data are used to estimate the model coefficients. However, unlike the Auto PD Model, the Auto LGD Model applies historical house price index based on FR Y-14Q region (as described above), while it applies the national unemployment rate to all observations. The model uses the historical values of the auto price index to estimate the model coefficients.

When applying the model coefficients to produce projected LGD, the model uses house price index and unemployment rate from the Stress Test Scenarios. The model procedure for projecting regional house price index is identical in the Auto LGD Model to the treatment in the Auto PD Model. For the purposes of projecting losses under the supervisory severely adverse scenario, the Board assumes that used auto prices (as measured by the auto price index) will decline by 10 percent. This cumulative 10 percent decline is projected to be distributed over all thirteen quarters of the scenario using a modified exponential decay function[554] with a parameter of 0.7, to front-load the decline in the early projection quarters and taper off by the final quarter. The projected decline in auto used car prices is similar to that experienced during the 2008 financial crisis.

[554] In general, an exponential decay function with a parameter of 0.7 indicates that in each quarter of the projection horizon, the decline in the index will be equal to 30 percent of the difference between the value of the index in that quarter and the minimum index value under the scenario. The exponential decay function is considered modified because the share of the total decline for each quarter, as projected by the exponential decay function, is rescaled such that the total decline over the thirteen quarters is equal to the 10 percent decline contemplated by the scenarios. Without this rescaling, because of the characteristics of exponential decay functions, the index would never reach its minimum value.

(4) Alternatives

Alternative Model Structures

The Auto LGD Model effectively leverages historical data reported on the FR Y-14Q to produce representative, reasonable projections of loss severity. Alternatives to the model are outlined in this section.

Unlike the Auto PD Model, the Auto LGD Model is developed at the segment level. This is supported both by data availability constraints and statistical considerations. The data availability constraints arise from the limited historic credit loss information available in the public domain. For instance, the Credit Bureau Data used to produce the Auto PD Model does not include information on recoveries that are needed for the computation of LGD. Loss information on loan level historical data can be found for auto loans that are included in auto asset-backed securities (ABS) portfolios; however, by construction, loans included in ABS portfolios are distinct from auto loans on the balance sheets of FR Y-14Q reporters, raising representativeness concerns.[555] The LGD model incorporates key risk drivers and produces loss estimates that fit well when applied to historical data.

The weighted least squares approach is applied to optimize fit and representativeness. The Auto LGD Model calculates the loss given that a loan defaults, and loan default risk is unequal across time and segment. Weighting by balance outstanding at charge-off ensures that the model appropriately captures the underlying relationships for the population of defaulted loans. Statistical model fit is substantially better when weighting is applied, compared to an unweighted alternative.

[555] When a loan is included in a security, it is no longer on the balance sheet of the original lender.

Alternative Covariates

With model structure determined, alternative variable selection and transformation is considered. Because of the segmentation of the data, finer breakouts are not available, even though there may be substantial variation within certain categories. In some cases, variables that could meaningfully impact recovery values are not reported in the FR Y-14Q, or reported data are insufficient for inclusion in the model. One notable case where a variable that could meaningfully impact recovery values is not reported is the differentiation of vehicle types. The FR Y-14Q instructions include summary variables for reporting the balance of loans in a segment that are classified as "car/van"; balances of loans in a segment that are classified as "SUV/truck"; and balances in a segment that are classified as "sport/luxury/convertible." However, as these variables are summary variables rather than segmentation variables, it is not possible given the current data structure to explicitly differentiate the different vehicle types within a segment.

While one possibility for including vehicle types in the Auto LGD Model would be to include the share of a segment that is in each category in the model, doing so creates inherently noisy estimates, for multiple reasons. First, since the categories are mixed together in each observation, the exact LGD within each category is unknown. Second, there is potential variation in the relative recovery rates for these vehicle types across time; for instance, the resale prices of SUVs compared to cars may change depending on fuel prices. Finally, variation in the recovery rates may be correlated with other factors. For instance, the share of vehicles categorized as "SUV/truck" has increased since the 2008 financial crisis. It is challenging to differentiate whether a negative coefficient on the share of loans in a segment in the "SUV/truck" category is due to inherently higher recovery rates or increased shares of these vehicles during a period where recovery rates were higher for other reasons. Based on these factors, the Board does not include this categorization in the Auto LGD Model. For vehicles of different fuel type (electric vs. internal combustion engine), the challenge to including these variables is more fundamental, as information about fuel type is not provided on the FR Y-14Q report. To include fuel type in a future Auto LGD Model, the reporting instructions would need to be changed to accommodate the inclusion of this field.

The macroeconomic variables proxy for household liquidity, household wealth, and used vehicle values, providing a robust overview of the economic conditions associated with LGD. In each case, values of the variable enter as comparisons with the one-year prior value, reflecting changes in conditions over the prior year. Shorter term changes (such as quarterly changes) are more susceptible to outliers and could reflect transient rather than sustained trends that could lead to less accurate and more volatile estimates of LGD. For the index of used vehicle prices obtained from a vendor, another possibility is to include the change in the value of the index since origination, allowing for the computation of an approximated refreshed loan-to-value ratio. Including this transformation would account for the fact that historic changes in the value of the index impact older loans, but not newer loans where the index values changed prior to the loan origination. Despite this potential benefit, the year-over-year percent change is maintained, for two reasons. First, the year-over-year change simplifies the approach operationally while also incorporating price changes in recent periods that meaningfully impact recovery values for most loans on which losses are being projected. Second, the limited segmentation of the loan age variable requires assumptions to assign the starting index value, which may meaningfully impact estimates in cases where there were large changes in the index value over the course of a year. Relying on the year-over-year change produces a consistent and interpretable value that can be applied to all loans.

Finally, it is possible that there are unobserved differences in credit quality across firms reporting FR Y-14Q, Schedule A.2 (U.S. Auto), which could lead certain firms to have persistently higher or lower LGD, even when accounting for other features. The Auto LGD Model does not directly account for any such unobserved differences in credit quality. One way to account for these differences is to directly include reporting firm as a variable in the model, using a statistical feature known as "firm fixed effects."[556] In fact, the reported data do show persistent differences in firm-level recoveries, so including these fixed effects would improve statistical model fit. Despite this, these fixed effects are not included in the model, to ensure consistent treatment of the model across firms. The restriction of the use of firm-specific fixed effects is consistent with the Stress Testing Policy Statement, which outlines that firm-specific fixed effects "are generally not incorporated in supervisory models to avoid the assumption that unobserved firm-specific historical patterns will continue in the future."[557] This modeling choice also allows for calculation of LGD for new reporters on the panel, which otherwise would not have an associated fixed effect.

(5) Questions

Question F3: How should the Board account for differences in recovery rates among different classes of vehicles (such as cars/vans vs. SUVs/trucks vs. sport/luxury, or internal combustion engine vs electric)? What additional information, if any, should the Board collect to ensure LGD is properly estimated for all vehicles?

Question F4: The Board is seeking comment on whether the projections of the auto prices during the projection horizon should be linked to the other variables in the scenario, compared

[556] In technical terms, fixed effects are implemented using a series of flags in the regression equation, each one representing a potential value of the variable (in this case, an individual firm).
[557] Policy Statement Section 2.4.

to the current model assumption that auto prices will decline by 10 percent regardless of the path of other scenario variables.

c. *Exposure at Default Model*

(1) Description

The Board bases the EAD for auto loans on the pattern of amortization of loans that ultimately defaulted[558] in the Credit Bureau Data, as reflected in Equation F4. The expected remaining balance is estimated using data on loans that ultimately defaulted between 2000 and the end of 2019,[559] to align with the definition in the Auto PD Model.

More specifically, remaining balance share is defined mathematically as in Equation F5:

Equation F5 – Auto EAD Remaining Balance Share

$$RB_{k,t}^{s} = \frac{\sum_{i=1}^{n} UPB_{i,k,t}^{s}}{\sum_{i=1}^{n} UPB_{i,k,0}^{s}}$$

where:

- *i* represents a loan, out of *n* loans total
- *s* represents the loan status at the start of the projection period, either current or delinquent
- *k* represents the loan age at the start of the projection period
- *t* represents the number of semi-annual periods elapsed between the start of the projection period and the default period
- $RB_{k,t}^{s}$ represents the remaining balance share for loan status *s* at age cohort *k* and time of default *t*;
- $UPB_{i,k,t}^{s}$ represents the unpaid principal balance at the time of default *t* for loan *i* with status *s* and age *k*;
- $UPB_{i,k,0}^{s}$ represents the unpaid principal balance at the start of the projection period for loan i with status *s* and age *k*; and
- The term " $\sum_{i=1}^{n}$ " indicates that the unpaid principal balances $UPB_{i,k,t}^{s}$ and $UPB_{i,k,0}^{s}$ are summed across all *n* loans with status *s* and age *k* at time *t* (or 0, depending on the term).

[558] The definition of default in the EAD model is consistent with the definitions elsewhere in the Auto Model, described in the introduction to Section F.ii.
[559] Considerations for using more recent data in the model are discussed in Section F.iii.a.(3).

The full remaining balance share matrix, denoted as $RB_{k,t}^{s}$, is shown in Table F4. The remaining balance share is identified based on the starting status, starting loan age, and time to default. For instance, if a loan is current at the beginning of the projection period, and is between 12 and 23 months old, and is projected to default between 13 and 18 months (5 and 6 quarters) after the start of the projection period, the balance at default will be assumed to be 83.4 percent of the balance reported for that loan at the start of the projection period:

Table F4 - EAD Matrix

	Loan Default Period						
LoanAge	0-6m	7-12m	13-18m	19-24m	25-30m	31-36m	37-42m
Current							
0-11m	100%	92.2%	84.8%	78.4%	70.1%	61.9%	54.8%
12-23m	100%	91.8%	83.4%	73.4%	64.9%	56.5%	49.1%
24-35m	100%	89.1%	78.1%	67.8%	58.3%	47.8%	38.4%
36-47m	100%	86.7%	73.1%	60.1%	47.6%	36.9%	29.5%
48m+	100%	79.5%	61.5%	48.3%	39.3%	34.3%	31.6%
Delinquent							
0-11m	100%	92.2%	86.7%	80.6%	71.2%	64.4%	56.9%
12-23m	100%	91.9%	85.1%	77.3%	68.6%	60.0%	53.7%
24-35m	100%	90.4%	81.7%	71.9%	61.7%	50.8%	41.6%
36-47m	100%	88.3%	76.6%	63.0%	53.2%	38.5%	30.8%
48m+	100%	79.4%	62.4%	48.2%	36.8%	30.5%	29.7%

(2) Support for Model Decisions

Since auto loans are generally fixed term, amortizing loans, outstanding balance is expected to decline as time passes from the origination of the loan. Auto loan terms are relatively short, compared to other products such as first-lien mortgages; as a result, amortization accounts for a relatively high share of starting balance over the stress test horizon. Because payments are not always made on schedule, especially in periods of stress, using simply the term and interest rate to calculate the amortization schedule risks understating the amount of balance remaining. Instead, historical data are used to calibrate the rate at which balances decline ahead of default.

The key characteristics used to define the remaining balance share matrix are the starting delinquency status of the loan, the loan age, and the elapsed period between the start of the calculation and default. Delinquency status impacts remaining balance share, especially for younger loans, as loans that are not making their full scheduled payments will pay down less balance and may incur fees —requiring future payments to apply to fees instead of going toward principal paydown. Loan age is a key driver of EAD, as for fixed rate loans, principal makes up a larger share of payments as the loan becomes more seasoned. Elapsed time since the start of the projection period also reduces EAD, as more time passing allows the borrower to make more payments on the loan prior to default. The seven semi-annual projection periods[560] together encompass the entire 13-quarter project period over which the Auto Model is used to project loan losses and provisions in the supervisory stress test.

The model is simple, easily interpretable, readily applicable to the reported FR Y-14Q U.S. Auto segments and can be implemented in a straightforward way. More complex implementations do not improve the model performance to justify the increase in complexity.

(3) Adjustments and Data Cleaning Steps

To be consistent with the Auto PD Model, the Auto EAD Model is estimated using the same data, limited to loans that eventually defaulted in the Credit Bureau Data from 2000 through 2019. Given the large size of the Credit Bureau Data, even with a 10 percent sample, the observation count remains sufficient to produce precise estimates. Similar to the Auto PD

[560] Similar to the PD model, semi-annual periods are used to align with the availability of the historical data used to estimate the remaining balance share.

Model, certain observations are filtered from the data to ensure reasonability and representativeness:

- Loans with a balance of $0 in the reference period
- Loans to international borrowers and borrowers in U.S. territories make up an immaterial share of firm portfolios and are not modeled by the Auto Model in the supervisory stress test.[561]
- Loans that are associated with RVs, residential mortgages, home equity lines of credit, or credit cards.[562]

(4) Alternatives

The Auto EAD Model is simple, interpretable, and produces reasonable estimates of exposed balance.

One alternative approach, even simpler, would be to simplify the model further and set EAD equal to principal balance at the start of the forecast period. This simple approach is more conservative and limits the need for additional assumptions for how fast balance will be paid down in an environment where there is significant non-payment. However, this approach would produce EAD projections that are unreasonably high, as empirical evidence shows that paid down balance on auto products account for a substantial share of balance, even close to default. Therefore, the simple approach is not justified for the supervisory stress test model, especially considering the readily available data that can be used to produce more accurate projections of EAD.

Other alternative approaches incorporate additional complexity. One factor that impacts the remaining balance share that is not incorporated in the Auto EAD Model is the loan term. In particular, as loan term gets longer, remaining balance shares generally increase meaningfully. In recent years, average loan terms have extended, as 6- and 7-year loan terms have become

[561] Losses on foreign auto loans and leases are projected in a separate model. *See* Section G for more details about the projection of losses for foreign auto loans and leases.
[562] Losses on these types of products are modeled by other retail models rather than the Auto Model.

increasingly common. This trend could lead to under-estimated remaining balance shares, and thus under-projected EADs. However, there are limitations to accounting for loan term based on the way data are reported. Loan term is frequently unavailable in the Credit Bureau Data; in the FR Y-14Q data, loan term is reported via summary statistics rather than in the data segmentation, requiring complex data transformations to incorporate loan age into the model and increasing the risk for input data errors. Performance testing of the model performed by the Board demonstrates that the statistical fit of the model, when applied to historical data (referred to as "back-testing analysis"), is reasonable, mitigating concerns on the exclusion of this variable.

Finally, macroeconomic characteristics are not included in the model. Instead, the impacts of the macroeconomic environment on auto loss rates are adequately captured through the Auto PD and LGD Models. Conceptually, auto loans are generally fixed rate installment loans with standardized payments; there is no credit line to draw on, and borrowers are contractually required to make payments. These factors limit the ability of borrowers to pay down slower during periods of economic stress. To assess empirically whether EAD is meaningfully impacted by the macroeconomic environment, the Board tested an alternative specification of the EAD model including both loan characteristics and macroeconomic variables, such as unemployment rate, but this analysis showed that the coefficients on macroeconomic variables were not statistically significant, indicating that balance paydown of auto loans is not very sensitive to the macroeconomic environment.

d. Model Integration and Projection

(1) Description

The model projects loss rates by applying the coefficient estimates from the PD, LGD, and EAD equations to specific loan segments from FR Y-14Q, Schedule A.2 (U.S. Auto). For each segment, the PD coefficients associated with that segment are applied. After the model is applied, projected PD rates are adjusted to produce unconditional projections of PD. This is needed because the model, in each quarter, projects the probability of default for loans in a segment that have not defaulted in any previous quarter. However, this fails to account for the loans that defaulted previously, after which they cannot default again. To make the adjustment, the Board multiplies the projected PD from the model by the share of loans in a segment that did not default in a previous quarter. This adjustment ensures that PD projections accurately measure the likelihood of a loan defaulting each quarter, referred to as the "unconditional PD."

For a given semi-annual projection period, projected unconditional PD is then multiplied by projected EAD to produce a semi-annual gross loss estimate. The semi-annual gross loss estimate is then divided by two, yielding a quarterly gross loss estimate which then is multiplied by LGD for that quarter to produce a quarterly net loss estimate. These quarterly loss estimates are applied to both quarters of the semi-annual period. These net losses are then aggregated up across all segments to produce portfolio level losses and divided by starting portfolio balances to produce what are referred to as "existing portfolio" loss rates.

"New origination" loss rates are projected similarly to existing portfolio loss rates. The portfolio characteristics are assumed to remain constant for new originations as the existing portfolio, consistent with the stress test assumption of a constant balance sheet, with the exception that new originations are assumed to be current (not delinquent) and the loan age field is reset to zero, reflecting that new originations cannot start as delinquent, and they by construction have loan age of zero as new loans. Two new origination loss rate paths are produced, the first starting in the first projection quarter and the second starting in the fifth projection quarter.

In addition to loss rates, portfolio paydown rates are produced for each quarter, separately for the existing portfolio and the two new origination portfolios. These paydown rates are reproduced in Table F5; a detailed explanation of their calibration can be found in Section F.ii.d.(2).

Table F5 - Paydown Rates

Projection Quarter	Paydown Rate - Existing Portfolio	Paydown Rate - First New Origination Portfolio	Paydown Rate - Second New Origination Portfolio
1	0.115692		
2	0.101924	0.115692	0.115692
3	0.089758	0.101988	0.101988
4	0.078892	0.089876	0.089876
5	0.069321	0.078954	0.078954
6	0.060771	0.069337	0.069337
7	0.053276	0.060702	0.060702
8	0.04676	0.053142	0.053142
9	0.041061	0.04655	0.04655
10	0.036064	0.040799	--
11	0.031691	0.035719	--
12	0.027825	0.031295	--
13	0.024406	0.027382	--

(2) Support for Model Decisions

Semi-annual to Quarterly Conversion

The model integration process is appropriate for applying the Auto PD, LGD, and EAD Models to compute quarterly loss rates. Because the Auto PD and EAD Models are estimated using semi-annual data, the odd quarters must be assigned losses based on data from the even quarters. Splitting the losses evenly between the two quarters is a simple implementation to reasonably fill in these missing periods. See Section F.iii.b for more discussion of the use of semi-annual estimates.

New Origination Loss Rates

The projection of the two new origination loss paths allows for the projection of losses on loans originated during the projection period. This is necessary to ensure that the model implementation is consistent with the constant balance sheet assumption. The inclusion of two new origination paths balances the goals of simplicity (more paths increase operational complexity and implementation cost) with robustness (new origination loss rates are expected to vary based on when in the projection they are originated).

Calculation of Paydown Rates

The paydown rates are calibrated using Credit Bureau Data covering the period 2008-2009. This period was chosen as it represents the 2008 financial crisis period, a historic period of significant economic stress, and therefore provides a reasonable proxy for expected conditions during the supervisory severely adverse scenario used in the stress test. Total portfolio balances among current loans in a given semi-annual period are compared to the balances of the same loans in the following semi-annual period. These totals are then aggregated across the periods used to estimate the six-month paydown rate, expressed as $PaydownRate_{6m}$. Then, the semi-annual paydown rates are converted to quarterly paydown rates (expressed as $PaydownRate_{3m}$) in Equation F6, as follows:

Equation F6 – Conversion of Semi-Annual to Quarterly Paydown Rate

$$PaydownRate_{3m} = 1 - \sqrt{1 - PaydownRate_{6m}}$$

This conversion assumes that the paydown rate path is exponential decay, such that a constant percentage of balance is paid down in every period. This assumption reasonably aligns with the behavior of paydown rates observed in the historical Credit Bureau Data described in the previous paragraph. This paydown rate is expected to be constant; however, the paydown table reflects that balances in each quarter decline by more than the paydown rate because there will be additional balance reductions due to charge-offs. For instance, if the quarterly paydown rate is 10 percent, 10 percent of balance would be expected to run off in the first quarter. If there were no charge-offs, 9 percent of the starting balance would run off in the second quarter (10 percent of the 90 percent remaining). However, if 2 percent of balance was charged off in the first quarter, only 8.8 percent of the starting balance would run off in the second quarter (10 percent of the 88 percent remaining). The charge-offs are projected using historical estimates of charge-off behavior under stress conditions. These calculations are repeated for each projection quarter, yielding in each quarter the share of the starting balance that is paid down in a given quarter. The calculation is the same for new originations as for the existing portfolio except that a different path of loss rates is assumed, given that new origination loss rates are slightly lower than existing portfolio loss rates.[563]

(3) Adjustments and Data Cleaning Steps

The Auto Model is applied to data reported on FR Y-14Q, Schedule A.2 (U.S. Auto). While firms are responsible for ensuring the completeness and accuracy of data reported in the FR Y-14 information collection, the Board makes efforts to validate firm-reported data and requests resubmissions of data where errors are identified. As outlined in earlier sections, if data

[563] For simplicity, the same paydown rate is applied to all new originations, unlike loss rates. Because loss rates have a small impact on the calibration of paydown rates, the impact of using only one paydown rate for new originations is immaterial.

quality remains deficient after resubmission, the Board applies conservative assumptions to a particular portfolio or to specific data, depending on the severity of deficiencies.

In general, all data that are reported accurately and completely are used to produce projections unless otherwise described in this section. However, the model does not directly project losses on auto leases (a category of product type reported on FR Y-14Q, Schedule A.2, U.S. Auto, Field A.1). This is due to the sparseness of the segment, which could lead to imprecise loss projections. Instead, loss rates for both auto loans and auto leases are determined based on the reported portfolio of auto loans. In particular, the loss rates produced by the Auto Model for auto loans are applied to the full population of auto loans and auto leases in the Retail Loss Aggregation process, described in Section F.ii.e.

Further explanation of the treatment of auto leases is available in Section F.ii.d.(4) and in Section F.iii.c.

(4) Alternatives

Semi-annual to Quarterly Conversion

The semi-annual projection is chosen based on the data frequency of the input data. Additionally, in implementing the semi-annual model, the Board does not account for the projected macroeconomic variables in the odd quarters of the projection period. However, the impact of this assumption is limited, as the scenarios envision the macroeconomic path over a longer time horizon. As long as the path of macroeconomic variables is sufficiently smooth, the projections will be reasonable. The assumption that the losses are divided evenly between the two quarters within a semi-annual period is a simplifying assumption. This potentially overstates the share of losses attributable to the second quarter of a semi-annual period, given that part of the balance will be paid down in the first projection quarter. However, as the impact of accounting for this factor was deemed by the Board to be trivial and extremely unlikely to notably impact projected loss rates in practice, the simple approach is applied.

Calculation of Paydown Rates

The calculation of portfolio paydown rates is a simple approach to account for the share of auto balance that is paid down in a given quarter. The calculation relies on historical data from the 2008 financial crisis period, to calibrate the estimate based on a period of economic stress. An alternative implementation would be to model the paydown rates based on characteristics of the portfolio, similar to how EAD is modeled in the loss calculation.[564] This could allow paydown rates to vary based on portfolio characteristics and potentially the economic environment. However, this approach would require the development of an additional model, contrary to the Stress Testing Policy Statement principle of simplicity.

Removal of Auto Leases

Auto leases are not included in the model projections due to sparseness. The instructions of the FR Y-9C and FR Y-14Q cause[565] only a small subset of auto leases, known as "sales-type leases and direct financing leases," to be reportable on FR Y-14Q, Schedule A.2 (U.S. Auto Loan). Other auto leases are known as "operating leases" and are not reported on this schedule but are instead reflected elsewhere in the supervisory stress test models.[566] Given these caveats, auto leases account for approximately 2 percent of total balances reported on the FR Y-14Q, Schedule A.2 (U.S. Auto). Because of the small size of this portfolio, the Board determined that, consistent with the principle of simplicity, it was not appropriate to develop a model framework

[564] The EAD paydown and portfolio paydown rates are not expected to be the same, as EAD is based on the balance rundown of loans that eventually default, while the paydown rates are based on current loans. The population of loans that eventually default is not representative of other loans in the data.

[565] Mechanically, auto leases are reported on FR Y-14Q, Schedule A.2 (U.S. Auto Loan) only if they meet the criteria for inclusion on FR Y-9C, Schedule HC-C, Item 10a.

[566] In cases of operating leases the lease is more similar to a rental agreement than a loan. Therefore, it is inappropriate to model the exposures as loan losses.

for projecting losses on auto leases. Instead, the models apply the loss rates calculated for auto loans to balances of both auto loans and auto leases. The Board considered alternative approaches, including developing a model specifically designed to apply to auto leases, or scaling auto lease losses based on historical relationships between auto loans and auto leases. Ultimately, a review of historical FR Y-14Q data determined that auto leases and auto loans have comparable net charge-off rates. More specifically, auto lease loss rates historically tend to be slightly lower than auto loan loss rates, but not substantially so, and not in all periods. Given the small balance of auto leases reported on the schedule, this assumption is unlikely to meaningfully impact stress test results. However, if balances of auto leases grow substantially in the future, or ongoing monitoring activities demonstrate a divergence between auto loan and auto lease loss rates, the Board may consider applying a separate model to project auto lease loss rates.

e. Retail Loss Aggregation

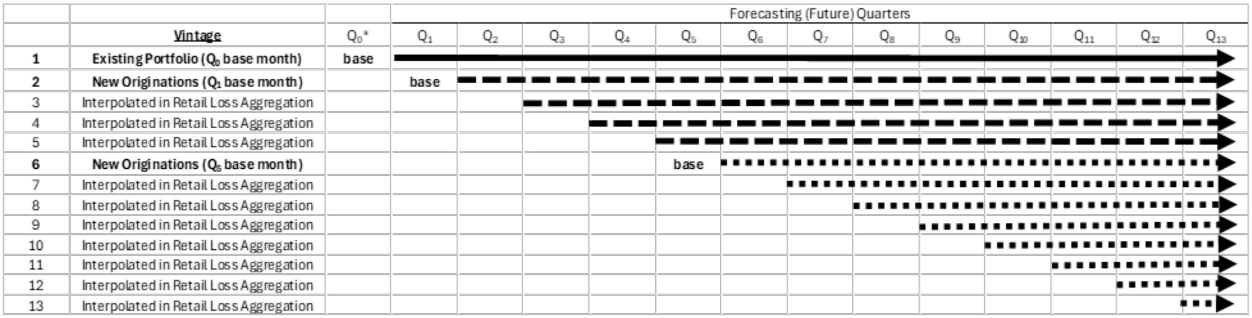
(1) Description

Retail Loss Aggregation refers to the process by which the Board uses the outputs described in the previous sections to produce final projections of loss dollars. In particular, the process begins with the reported portfolio balances and the projected loss rates and projected payoff rates described in Section F.ii.d for each quarter for each firm participating in the supervisory stress test reporting data on FR Y-14Q, Schedule A.2 (U.S. Auto), for the existing portfolio as well as two projected new origination portfolios. From there, the Board applies a series of calculations and adjustments, described in detail below. The output of the Retail Loss Aggregation process is a final projection of loss dollars for each firm in the portfolio in each quarter.

In Retail Loss Aggregation, the projected loss rates are assigned to the balances of auto loans and auto leases produced by the balance sheet line-item projections calculator based on data reported in FR Y-14Q, Schedule M.1 (Balances).[567] In particular, auto loan balances are taken from line item 4a, column A (CALBR663) from this schedule, while auto lease balances are taken from line item 4d, column A (CALBR675) from this schedule. Existing portfolio loss rates are multiplied by this balance in each of the 13 projection quarters to produce existing portfolio loss dollars. New origination loss dollars are calculated by applying the new origination loss vectors to the projected new origination amounts. New origination amounts in each quarter are projected as the sum of the dollar amounts of paydowns and the losses in that quarter on the existing portfolio, as well as any additional losses or paydowns on new originations from previous quarters. New originations in the first through fourth projection quarters are assigned the new origination loss rate path associated with originations in the first projection quarter; new originations in the fifth through thirteenth projection quarters are assigned the new origination loss rate path associated with originations in the fifth projection quarter.[568] Total quarterly loss dollars are calculated as the sum of losses on the existing portfolio and any new origination portfolio originated by a given point in the projection period. A visual depiction of this process is in Figure F1:

[567] *See* Section A in the Aggregation Models Description (Balances Model).
[568] The determination to use two new origination loss rate paths, corresponding to the first and fifth projection quarter, is described in Section F.ii.d.

Figure F1 - Description of Existing and New Origination Loss Rates



In this visual, each row refers to a vintage of new originations and each column represents a quarter of the supervisory stress test projection period, starting from Q_0—the starting point of the projection. The existing portfolio uses the existing portfolio loss rate (represented by the solid line); the first four quarters of new originations use the first new origination loss rate vector (represented by the dashed line); and the fifth and following quarters of new originations use the second new origination loss rate vector (represented by the dotted line). For example, new originations in the fifth projection quarter use the second new origination vector, where the first quarter of loss rates are applied in the sixth projection quarter; the second quarter of loss rates are applied in the seventh projection quarter, and so on. New originations in the sixth projection quarter use the second new origination vector, where the first quarter of loss rates are applied in the seventh projection quarter; the second quarter of loss rates are applied in the eighth projection quarter, and so on.

The above process produces loss dollars for firms reporting data on the FR Y-14Q, Schedule A.2 (U.S. Auto Loan); however, certain firms who report auto balances on FR Y-14Q, Schedule M.1 (Balances) do not report on the FR Y-14Q, Schedule A.2.[569] For firms not

[569] Firms are required to report FR Y-14Q, Schedule A.2 (U.S. Auto) if portfolio balances are material, as defined in the FR Y-14Q instructions. Firms with portfolio balances that are below the materiality threshold have the option of submitting or not submitting the schedule. The Federal Reserve uses reported data to produce loss estimates for firms whenever possible, even if the reporting institution is below the materiality threshold.

reporting the FR Y-14Q, Schedule A.2 that are not required to do so, portfolio balances, balances produced by the balance sheet line-item projections calculator based on data reported in FR Y-14Q, Schedule M.1 (Balances)[570] are assigned the loss rate paths (of the existing and new origination portfolios) of the firm with the 50th percentile loss rate among firms reporting FR Y-14Q, Schedule A.2.[571] For firms not reporting the FR Y-14Q, Schedule A.2 that are required to do so, portfolio balances are assigned the loss rate path of the firm with the 90th percentile loss rate among firms reporting FR Y-14Q, Schedule A.2. In either case, if no firm is exactly at the 50th or 90th percentile, respectively, the firm with the loss rate immediately above this level is used.

Total losses created by the Retail Loss Aggregation process are used in the downstream Provisions Model[572] to produce estimates of provisions.

(2) Support for Model Decisions

The Retail Loss Aggregation process produces loss estimates using a simple, consistent process across all retail portfolios. This process ensures adherence to principles of the supervisory stress test, including simplicity, consistency, robustness, and the assumption of a constant balance sheet throughout the forecast period.

(3) Adjustments and Data Cleaning Steps

Generally, no data adjustments are needed for this step. However, if a firm's submitted data are too deficient to produce a supervisory loss estimate, the Board assigns a high loss rate (based on the 90th percentile, as described above) to the portfolio balances based on supervisory projections of auto losses for other firms.

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[570] *See* Section A in the Aggregation Models Description (Balances Model).
[571] In this context, "loss rate" refers to total loss dollars divided by initial portfolio balances. Percentiles are calculated by summing the loss rates over the 13 projection quarters.
[572] *See* Section B in the Aggregation Models Description (Provisions Model).

(4) Alternatives

A range of alternatives are theoretically available both for determining the level of new originations and the treatment of missing data and immaterial portfolios. However, the chosen approach is the approach that is consistent with certain assumptions applied broadly in the supervisory stress test—importantly, the assumption of a constant balance sheet through the projection period and the treatment of missing data and immaterial portfolios. The Retail Loss Aggregation framework is chosen to produce reasonable, consistent projections that are consistent with the Stress Testing Policy Statement.

iii. Key Assumptions for the Auto Model

a. Representativeness of Estimation Data

The Credit Bureau Data used to estimate the Auto PD and EAD Models is based on a representative sample of U.S. consumers with both a credit file and social security number. Since the model is used to project losses on the auto loan portfolios of institutions subject to the stress test, the process implicitly assumes that the data used to estimate the model are representative of the data for which the model is projecting losses. If the sample of loans used to estimate the model is more or less risky than the loans for which the model is projecting losses, across characteristics that are either unobservable or not included in the model, this could lead to inappropriately low or high loss projections in the stress test. The Auto Model partially accounts for this by incorporating the variables deemed by the Board to be the most important factors associated with auto loan default risk into the Auto PD Model; however, due to data limitations and unobservable factors, representativeness is still a concern. Nevertheless, considering that important factors are incorporated into the model, the Board determined that due to the long time series, coverage of important fields, and loan-level structure of the Credit Bureau Data, the advantages of using the data outweigh any drawbacks when compared to the use of a nationally representative dataset. The specific representativeness issues are detailed below.

(1) Inclusion of Auto Leases in Estimation Sample

One representativeness concern arises from the inclusion of auto leases in the PD and EAD estimation data. The model is not applied to auto leases in projection, and historically, auto leases default at lower rates compared to auto loans and may have different EAD as well. Therefore, including auto leases could lead to loss projections that understate the riskiness of the portfolio. However, this concern is mitigated by the fact that auto leases comprise just 10 percent of the estimation data sample; therefore, analysis performed by the Board has shown that coefficient estimates and projected loss rates do not substantially differ whether or not auto leases are included in the estimation sample.

(2) Representativeness of Lenders

As detailed in Section F.ii.a.(3), an additional representativeness concern arises from the population of lenders included in the Credit Bureau Data. The Board does not observe individual lenders in the Credit Bureau Data.

As noted in the previous discussion of this issue, the Board determined that relying on the Credit Bureau Data is reasonable. If more information becomes available on differences in the behavior of loans between those from institutions subject to the stress test and those from other lenders, the Board may consider incorporating additional information into the model to account for these differences.

(3) Exclusion of Pandemic Era Data

A final representativeness concern is related to the periods of data used to fit the model. The data used to produce the model estimates (the “estimation sample”) does not include data in

2020 and after, due to unique challenges associated with the behavior of the portfolio given the economic environment during the COVID-19 pandemic. During this period, the unemployment rate increased at a historic pace and then declined sharply from its peak, while auto loan default rates and loss rates remained low. This combination of high unemployment and low default and loss rates is contrary to expectations and contrary to previously observed paths of default rates and loss rates during other periods of elevated unemployment rates. This outcome can likely be explained by the historic level of income support provided during the COVID-19 pandemic, which led to borrowers' income and savings levels remaining high despite higher unemployment. These relationships likely reflect the unique circumstances of the COVID shock, and will likely not be reflective of future behavior, as discussed below.

Academic research corroborates the view that the economic distortions in 2020 and the years following are significant, and that the observed relationships between the economic environment and borrower behavior during this period are unique to it. For example, Stock and Watson (2025) find that the COVID shock was notable, but had "largely disappeared by late 2022."[573] This finding raises concerns that if data covering 2020-2022 are used to estimate the model coefficients, these coefficients may be impacted by the distortions that caused these unusual observed relationships.

While the concerns with including this period of data are significant, ending the estimation in 2019 could potentially lead to model parameters that do not reflect the current portfolio, as recent periods are not included in the model estimation. This could lead to model projections that do not accurately reflect the true level of risk.

[573] Stock, J. and M. Watson (2025). "Recovering from COVID," NBER working paper 33857.

To assess this risk, the Board has tested incorporating data from more recent periods into the Auto PD Model, while applying a treatment to data during the COVID-19 pandemic period to avoid the model from being unduly impacted by the unemployment rate volatility in 2020. Results indicated that the projected losses under the model with the extended sample of data were slightly higher than those produced by the supervisory stress test model, but the changes were sufficiently small that they are unlikely to materially affect the stress capital buffer or stress test results for almost all firms which have participated in recent stress tests. The small size of these differences suggests that the model projections are not substantially impacted by the exclusion of recent periods of data.

b. Semi-annual Calculation

As detailed in Section F.ii.a and Section F.ii.c, due to limitations in the historical data used to estimate the model, PD and EAD projections are produced semi-annually. These semi-annual projections are divided evenly between the two quarters they comprise.

This process is reasonable as long as there are not large changes in the dynamic variables, such as the macroeconomic data, within the semi-annual period. Analysis performed by the Board indicates that this risk of unreasonable results from this assumption is low, as the supervisory stress test scenarios generally use relatively smooth macroeconomic paths over the course of a hypothetical recession.

c. Auto Lease Treatment

As discussed in detail in Section F.ii.d, the Board does not directly model domestic auto leases reported on FR Y-14Q, Schedule A.2 (U.S. Auto), instead assuming that auto lease loss rates for a firm will be identical to that firm's loss rates for auto loans. Auto leases account for just 2 percent of balances reported on FR Y-14Q, Schedule A.2,[574] and the population of the segment data is sparse. Historical data indicates that auto leases generally have lower default rates and net charge-off rates compared to auto loans.

d. Questions

Question F5: The Board seeks comment on whether to continue to assign auto leases the same loss rate as auto loans at a given firm, as opposed to calculating and applying a unique loss rate for auto leases.

Question F6: The Board seeks comment on what factors or variables should be included in a model used to project losses on auto leases, if the Board were to adjust the process for auto leases.

iv. Alternatives to the Auto Model

The Auto Model uses an expected loss framework to produce projections of losses on consumer loans held for investment at amortized cost that are extended for the purpose of purchasing new and used automobiles and light motor vehicles, as defined by the FR Y-9C. Alternatives modeling choices for the individual model components are discussed earlier in this document; this section describes alternatives to the expected loss framework. Two alternatives are discussed: a *scalar approach* and a *net charge-off* approach.

Under a scalar approach, a single loss rate path is assigned to each firm reporting auto balances. The scalar can be calibrated based on historical data to align with expectations during a stress period. The scalar approach maximizes consistency by treating loans identically across firms and has the additional advantage of a simple implementation. However, a scalar approach does not allow for differentiation of loss rates based on observable risk characteristics, such as

[574] As discussed previously, only certain auto leases are included in this schedule.

differences in product type and credit score, and does not allow loss rates to vary based on macroeconomic scenario inputs. Given these drawbacks, a scalar approach was not chosen for this model.

Under a net charge-off approach, projected charge-offs are estimated directly using the segment-level input data. This approach is used for the Other Retail Model[575] in the supervisory stress test. Direct projection of net charge-offs is simple and interpretable, and in-sample fit is generally strong when incorporating a structure where the projected net charge-off rate in a quarter is based on the observed net charge-off rate in the previous quarter, as well as other factors ("autoregressive model structure"). However, a trade-off of this approach is that the autoregressive model structure tends to crowd out the impact of other variables—such as loan-level characteristics and macroeconomic variables—and may have less validity out of sample. As a result, a net charge-off model may suffer from inappropriately limited sensitivity to the macroeconomic environment. Additionally, the projected net charge-off model is constrained in its ability to incorporate certain dynamics. For instance, while the Auto Model applies different coefficients to current and delinquent loans, reflecting that drivers of risk are different for loans that are current versus loans that are delinquent, a net charge-off model would not be able to account for these differences. While net charge-off models can produce reasonable projections in cases where loan-level data are not available, the expected loss approach allows for the incorporation of more factors and appropriately identifies the different risk factors in the subcomponents (PD, LGD, EAD).

[575] *See* Section G.

G. Other Retail Model

i. Statement of Purpose

The Other Retail Loss Model (Other Retail Model) is used to project loan losses and provisions on loans, as measured at amortized cost, for a range of loan categories, referred to throughout this document as “portfolios.” These portfolios include (1) Domestic Small Business loans; (2) Domestic Other Consumer loans; (3) Student loans; (4) Domestic Small Business and Corporate Credit Cards; (5) Retail Non-Purpose loans;[576] (6) International Other Consumer loans; (7) International Bank and Charge Cards; (8) International First Mortgages; (9) International Home Equity loans; (10) International Small Business loans; (11) International Small Business and Corporate Credit Cards; and (12) International Auto loans and leases. The Board generally defines these portfolios based on the FR Y-9C classifications and models most of the 12 loan portfolios separately.[577] Losses projected on these portfolios are distributed across loan categories in the Stress Test Results document as shown in Table G1:

Table G1 - Other Retail Loan Portfolios and Disclosure Categories

Portfolio	**Disclosure Category**
Domestic Small Business loans	Commercial and industrial
Domestic Other Consumer loans	Other consumer
Student loans	Other consumer
Domestic Small Business and Corporate Credit Cards	Commercial and industrial
Retail Non-Purpose loans	Other consumer
International Other Consumer loans	Other consumer
International Bank and Charge Cards	Credit cards
International First Mortgages	Other loans
International Home Equity loans	Other loans
International Small Business loans	Commercial and industrial

[576] Non-purpose loans are loans collateralized by securities made for any purpose other than purchasing or carrying securities.
[577] The International Bank and Charge Card portfolio and the International Small Business and Corporate Credit Card portfolio use a shared model that outputs results separately for the two portfolios.

Portfolio	Disclosure Category
International Small Business and Corporate Credit Cards	Commercial and industrial
International Auto loans and leases	Other consumer

The Other Retail portfolios cover a broad range of lending that is not accounted for by other supervisory stress test models. While the balances of the individual portfolios are small as a share of the total balance of loans modeled in the stress test, together they can meaningfully impact the capital position of firms engaged in these forms of lending. During and immediately following the 2008 financial crisis, losses on Other Retail loans, as reported in the historical data reported on the FR Y-14Q, were high, demonstrating the risk that these loans could take on substantial losses during a prolonged period of economic distress. Among firms participating in the 2025 Stress Test, approximately 8 percent of the loan balances and 13 percent of loan losses stem from Other Retail loans. Given these factors, the Board models these portfolios using a shared framework that produces reasonable loss projections that appropriately reflect variation in risk levels while avoiding unnecessary complexity and limiting the reporting burden associated with these portfolios.

In general, for the Other Retail portfolios, the Board projects a net charge-off rate for each portfolio in each quarter. Among larger portfolios with historical loss rates that are substantial and sensitive to the macroeconomic environment, net charge-off rates are projected using a regression framework that accounts for portfolio characteristics, the macroeconomic environment, and net charge-off rates reported or projected in the previous quarter. The regression models used for the Other Retail portfolios are calibrated using historical, industrywide data combined into aggregated categories, referred to as segments. As this document will describe in detail, these segments are determined based on the factors that are most associated in the historical data with differences in expected losses; the segment-level models are parsimonious and allow the Board to project loan losses in a uniform way despite potential differences in composition within and across portfolios for each firm. Regression Models are further sub-divided into "Domestic" and "International" regression models,[578] corresponding to the characteristics of the respective portfolios.

For certain other portfolios, the Board determined that a regression model structure is not appropriate, either because the portfolios are so small that the data used to produce model parameters are too sparse to produce reliable outputs, the current balances of the portfolio are too small to notably impact stress test results, or because sufficient historical loss information is not available. In these cases, the Board instead projects a single net charge-off rate path for all balances within the portfolio by applying scalar models. For scalar models for which industry historical net charge-off rate data are available, loss rate projections are based on these historical data, while accounting for the expectation that losses will be elevated during periods of economic stress compared to other periods. In cases where historical data are not widely available, the Board instead applies loss rate projections based on projections for other loan categories in the supervisory stress test with similar characteristics, economic theory, and other factors, while ensuring that loss rate projections are consistent with the principle of conservatism from the Stress Testing Policy Statement, given uncertainty associated with the loss projections of loans for which limited historical loss information is available. A detailed description of the calibration of scalar model loss rates is available in Section G.ii.a.(3).

[578] International regression models are also referred to throughout this document as the "International Cards Model," as the Portfolios made up of credit cards are the only international retail loans that use a Regression Model. See Table G2 for more details. Domestic regression models are often referred to as "Domestic Models" throughout this document for brevity.

Table G2 presents how the various Other Retail portfolios are mapped to the model types. A detailed explanation for how the Board maps these loan types to these model types is available later in this document.

Table G2 - Mapping of Other Retail Portfolios to Model Types

Model Type	Model Sub-Type	Portfolios
Regression	Domestic	Domestic Small Business loans Domestic Other Consumer loans Student loans[579] Domestic Small Business and Corporate Credit Card loans
	International (or "International Cards")	International Bank and Charge Cards International Small Business Corporate Credit Cards
Scalar		International Other Consumer loans International First Mortgages International Home Equity loans International Small Business loans International Auto loans Retail Non-Purpose loans

To project loss dollars, these projected net charge-off rates (alternatively referred to as loss rates throughout this document) are assigned to a firm's total balance reported in that portfolio (as reported on the FR Y-14Q, Schedule M, Balances).[580] Consistent with the Stress Testing Policy Statement, the Other Retail models assume that the balance of loans in each portfolio will remain constant throughout the stress test horizon.

[579] As described in Section G.ii.a.(3), the regression model is applied only to private student loan balances. Student loan balances from government programs are assigned a scalar loss rate.

[580] Consistent with other models, the Other Retail models assume that the balance of loans in each portfolio will remain constant throughout the stress test horizon. To implement this assumption, the models assume that there will be new originations equivalent to the amount of balance charged off in the previous quarter, and these new originations are assigned the same loss rate as the existing portfolio in a given quarter.

As discussed in more detail in Section G.ii.a.(3), historical macroeconomic data are sourced from government agencies. To project losses on Other Retail loans, the models apply projected values from the supervisory stress test scenarios.

This section is organized as follows. First, in Section G.2.a, the models are described in detail. With the models described, the document next provides support for the various assumptions and decisions in the model in Section G.2.b. Following that, a detailed description of the data used to calibrate the model parameters and project losses using these models is presented in Section G.2.c. Finally, alternatives to the models are discussed in Section G.2.d, and key assumptions are addressed in further detail, in section G.3.

ii. Model Description

As described in Section G.i, the Other Retail models are used to project loan losses and provisions in the supervisory stress test for the portfolios listed in Table G1. The models are used to project results for a wide array of portfolios with very different features; furthermore, individual portfolios such as “Other Consumer” encompass a broad range of lending within the portfolio definition. The portfolios are united by the fact that they are not captured by the other supervisory stress test models that estimate Retail loan losses. Given that it would be challenging to create a unique framework for each form of lending captured by the Other Retail portfolios, especially as these portfolios encompass a wide range of lending, the Board uses a shared framework to model these portfolios. A “top-down” approach is used to produce accurate projections using this shared framework. See Section G.ii.b.(1) for additional discussion of the choice to use a “top-down” modeling approach.

Unlike other loan loss models used in the supervisory stress test that use an expected loss approach, the Other Retail models directly model the portfolio-level net charge-off rate based on features of the portfolio and the macroeconomic environment.[581] Net charge-off rates refer to the share of the balance in a given portfolio that is charged-off in a given quarter, net of any recoveries received in that quarter.

The rest of this model description discusses the models in detail. The process for projecting losses for the Other Retail portfolios occurs in two steps:

1) First, net charge-off rates are projected for each of the 12 portfolios.
2) Then, portfolio-level losses (in dollars) are calculated by multiplying the projected net charge-off rates by the balances projected by the balance sheet line-item projections calculator.[582]

This process is further detailed in the subsections below. First, the theoretical design of the models is described, separately for the different types of models outlined in Table G2. Next, the data and methodology used to estimate the models is described. Finally, the process used to apply the estimated models to project losses is described.

a. Description

(1) Model Design

Regression Models

As discussed in Section G.i, the Board uses regression models for portfolios that are sufficiently large—and for which there is sufficient historical loss data—to project net charge-off rates based on reported data and projected macroeconomic characteristics with sufficient precision. In particular, each of the regression models projects net charge-off rates for associated

[581] As described later in this section in Section G.ii.a.(4) and in further detail in Section B of the Aggregation Models Description (Provisions Model), the Board applies an adjustment to the calculation of allowances to account for differences between net charge-off models and expected loss models.
[582] For more information, see Section A of the Aggregation Models Documentation (Balances Model).

portfolios for each firm in each quarter based on the firm's previous value of net charge-off rate, characteristics of the portfolio, and the macroeconomic environment. A detailed explanation of how the Board determined which portfolios are good candidates for regression models is available in Section G.ii.b.

While both Domestic and International portfolios use regression structures, the details are somewhat different, due to differences in the characteristics of the portfolios that justify designing the models differently. For this reason, the design of the Domestic and International Model is described separately.

Domestic Models

The Domestic Models, used for the portfolios indicated in Table G2, project net charge-off rates for each firm in each quarter using linear regressions.[583] The linear regression equations are estimated separately for each of the four portfolios. Each equation accounts for portfolio characteristics by dividing the portfolio into different segments, chosen based on analysis of historical FR Y-14Q data to differentiate net charge-off rate projections based on the most important determinants of risk in a portfolio. Within each segment, the models use the firm's net charge-off rate in the previous quarter to account for the fact that certain firms have persistently higher or lower net charge-off rates than other firms. Finally, macroeconomic variables are included to account for the expectation that net charge-off rates will increase in periods of economic stress. Mathematically, the regression can be described as in Equation G1:

[583] Linear regression is a type of statistical model that uses a mathematical equation to project an outcome variable (in this case, net charge-off rate) based on other variables (in this case, previous values of net charge-off rate, portfolio characteristics, and the macroeconomic environment). Linear regressions are simple to implement, easy to interpret, and have beneficial statistical properties that make them good choices for use in projecting net charge-off rates for the Other Retail portfolios.

Equation G1 – Domestic Model Regression

$$NCO_{i,k,t} = \alpha_k + \varphi NCO_{i,k,t-1} + \beta X_t + \epsilon_{i,k,t}$$

where:

- *i* represents the firm (of *N* total covered firms)
- *k* represents a segment of loans within the portfolio (of *K* total segments)
- *t* represents time in quarters (of *T* total periods)
- $NCO_{i,k,t}$ is the outcome variable, the net charge-off rate in a given quarter
- α_k represents the average risk level of a given segment ("segment fixed effect")
- $NCO_{i,k,t-1}$, is the net charge-off rate in the previous quarter; the impact of the previous quarter's net charge-off rate on the current quarter's net charge-off rate is determined based on the parameter φ, its coefficient
- X_t is a set of macroeconomic variables used, which differ by equation (see Table G6 for a full list of macroeconomic variables used in each model); the impact of these variables on net charge-off rate is determined based on the parameter β, its coefficient; and
- $\epsilon_{i,k,t}$ is an error term, a standard feature of linear regression models. This error term is used to capture differences in net charge-off rates not accounted for by the other terms in the model. On average, this term is zero, meaning that the model is not arbitrarily biased upwards or downwards after accounting for the variables included in the model.

The Domestic Models use parsimonious specifications that align with the stress testing principle of simplicity. Furthermore, the Models produce results that are both reasonable and easily interpretable. While more complex specifications are possible (see Section G.ii.d.(1)), adding additional complexity generally does not increase the ability of the Model to produce accurate, reasonable projections of net charge-off rates. Additional support for the model structure is available in Section G.ii.b.(1). Details on the exact specification of the Domestic Model and the methods used to estimate its parameters are available later in this section, in Section G.ii.a.(3).

International Model

The International Cards Model is used to project net charge-off rates for both the International Bank and Charge Card and International Small Business and Corporate Credit Card portfolios. A single model is used to project losses on each of the two portfolios, calibrated based on historical data from both portfolios. While the individual portfolios—particularly the International Small Business and Corporate Credit Cards portfolio—have relatively sparse historical data, the Board determined that it was appropriate to use a regression model anyway, for the reasons described below. First, the two portfolios are relatively material and a scalar model that failed to account for differences across firms or across time could result in notably inaccurate loss projections, compared to the other international portfolios that use scalar models. Second, the Board determined based on its experience and expertise, and based on a review of historic data reported on FR Y-14Q, Schedule A.3 (International Cards), that the two portfolios are sensitive to similar factors. With the two portfolios together, there is sufficient historical data to produce a reasonable model. Therefore, these portfolios use a shared model, allowing the Board to leverage historical relationships between variables for either portfolio to produce forward-looking projections. Meanwhile, variables are included within the model to differentiate balances between the two portfolios, allowing the model to capture persistent differences in net charge-off rates between the two portfolios. Performance testing conducted by the Board, including measures of statistical fit and tests of the accuracy of the model when applied to historical data, bolster the case for using a regression model for these portfolios.

Similar to the Domestic Models, the International Cards Model uses a linear regression framework; however, unlike the Domestic Models, which project net charge-off rates using a single equation per portfolio, the International Cards Model projects the net charge-off rate in two steps using two linear regressions. The first equation projects the share of balance that is delinquent (or "delinquency rate") for a given firm in a given quarter, where credit cards are defined as delinquent when they are 60 or more days past due.[584] This equation uses portfolio

[584] Support for the Board's decision to treat loans as delinquent based on when they are 60 or more days past due is available in Section G.ii.b.(2).

characteristics, the previous share of delinquent loans, and the macroeconomic environment to project the delinquency rate in a given quarter. This delinquent share, as well as the net charge-off rate in a given quarter, portfolio characteristics, and the macroeconomic environment, are used to project the next quarter's net charge-off rate. Similar to the Domestic Models, the model divides the portfolio into a small number of segments to account for persistent differences in net charge-off rates among different loans within the portfolio. In the International Cards Model, segments are defined based on portfolio (International Bank and Charge Card or International Small Business and Corporate Card) and geographic region; see Table G5 for a detailed explanation of the segments included). Mathematically, the equations can be described as in Equations G2 and G3:

Equation G2 – International Cards Model Delinquency Equation

$$DEL(60+)_{i,k,t} = {\rho_1}^{DEL} DEL(60+)_{i,k,t-1} + \alpha_k^{DEL} + \quad \varphi^{DEL} propscore_{k,t} + \beta^{DEL} X_t + \varepsilon_{i,k,t}^{DEL}$$

where:

- i represents the firm (of N total covered firms)
- k represents a segment of loans within the portfolio (of K total segments)
- t represents time in quarters (of T total periods)
- $DEL(60+)_{i,k,t}$ is the share of balance 60 or more days past due in a given quarter
- $DEL(60+)_{i,k,t-1}$ is the share of balance 60 or more days past due in the previous quarter; the impact of the previous quarter's delinquency rate on the current quarter's delinquency rate is determined based on the parameter ${\rho_1}^{DEL}$, its coefficient
- α_k^{DEL} represents the average risk level of a given segment ("segment fixed effect") in the delinquency equation
- $propscore_{k,t}$ represents the share of loans in a segment that have credit scores[585] as of origination (1) less than or equal to 620; (2) greater than 620; or (3) missing or unknown; the impact of these shares on delinquency is determined based on the parameter φ^{DEL}, which represents the coefficients on these terms
- X_t is a set of macroeconomic variables used, which differ by equation (see Table G7 for a full list of macroeconomic variables used in each model); the impact of these variables on

[585] Credit score ranges are for loans for which FICO® was either the original credit score used at origination or the score to which an internal credit score or commercially available credit score was mapped. *See* FR Y-14Q instructions at 23.

net charge-off rate is determined based on the parameter β^{DEL}, which represents the coefficients on these terms; and
- $\epsilon_{i,k,t}$ is an error term, a standard feature of linear regression models. This error term is used to capture differences in net charge-off rates not accounted for by the other terms in the model. On average, this term is zero, meaning that the model is not biased toward unreasonably high or low projections.

Equation G3 – International Cards Model Net Charge-off Equation

$$NCO_{i,k,t} = \rho_1{}^{NCO} \quad NCO_{i,k,t-1} + \rho_2{}^{NCO} \quad DEL(60+)_{i,k,t-1} + \alpha_k^{NCO} + \beta^{NCO} X_t + \varepsilon_{i,k,t}^{NCO}$$

where:

- *i* represents the firm (of *N* total covered firms)
- *k* represents a segment of loans within the portfolio (of *K* total segments)
- *t* represents time in quarters (of *T* total periods)
- $NCO_{i,k,t}$ is the net charge-off rate a given quarter
- $NCO_{i,k,t-1}$, is the net charge-off rate in the previous quarter; the impact of the previous quarter's net charge-off rate on the current quarter's net charge-off rate is determined based on the parameter $\rho_1{}^{NCO}$, its coefficient
- $DEL(60+)_{i,k,t-1}$ is the share of balance 60 or more days past due in the previous quarter; the impact of the previous quarter's delinquency rate on the current quarter's net charge-off rate is determined based on the parameter $\rho_2{}^{NCO}$, its coefficient
- α_k^{NCO} represents the average risk level of a given segment ("segment fixed effect") in the net charge-off rate equation
- X_t is a set of macroeconomic variables used, which differ by equation (see Table G7 for a full list of macroeconomic variables used in each model); the impact of these variables on net charge-off rate is determined based on the parameter β^{NCO}, which represents the coefficients on these terms; and
- $\epsilon_{i,k,t}$ is an error term, a standard feature of linear regression models. This error term is used to capture differences in net charge-off rates not accounted for by the other terms in the model. On average, this term is zero, meaning that the model is not arbitrarily biased upwards or downwards after accounting for the variables included in the model.

Altogether, the International Cards Model uses a slightly more complex model structure to project net charge-off rates for the International Cards portfolios. While the more parsimonious approach produced reasonable results for the Domestic Models, the approach used for the Domestic Models is unable to reliably project net charge-off rates for the International

Cards portfolios, likely due to the large differences in historical net charge-off rates for different firms that are not explainable based on observable data.

Therefore, the International Cards Model incorporates two features not used in the Domestic Models, both of which allow the model to account for additional differences across firms not captured by other data fields without adding so much complexity that they reduce interpretability. These features are described below:

- Two-equation structure: The two-equation structure allows the model to account for not only the likelihood that differences in historical net charge-off rate will persist in the future, but that differences in historical delinquency rates will persist, and that higher delinquency rates will be reflected in the future with higher net charge-off rates.
- Inclusion of additional portfolio characteristics: Both the Domestic and International Model use portfolio characteristics to segment the data into more and less risky segments. Incorporating more granular segments into the models allow the models to account for different expected net charge-off rates for loans with different features. However, adding too many segments can lead to certain segments becoming sparse, reducing the precision on model projections for these segments. For the International Cards Model, in addition to portfolio and geographic region, which are used to segment the model, the Board determined that the share of balances in different credit score categories was a meaningful predictor of net charge-off rates. However, because certain categories—namely the low credit score (less than or equal to 620 FICO® or equivalent) and missing credit score categories—are small, instead of using credit score categories to further segment the Model, the Model instead simply includes the share of loans in each credit score category in a given segment.

Details on the exact specification of the International Cards Model and the methods used to estimate its parameters are available in Section G.ii.a.(3). Further support for the model structure is described in Section G.ii.b.(1).

Scalar Models

Scalar models are used to project net charge-off rates for the remaining six portfolios in Table G2. These models are referred to as scalar models because they assume a constant net charge-off rate for each portfolio. Unlike the regression models, the scalar models do not allow for the differentiation of net charge-off projections based on differences in portfolio characteristics. However, as will be further described in Section G.ii.b.(2), scalar models are used for these portfolios due to some combination (varying by portfolio) of sparseness of reported data and limited balances in the portfolio reducing the impact of loss projections in these portfolios on stress testing results. In most portfolios using scalar models, sparse data are the direct result of the fact that the respective portfolios are small in both current and historical balance and limited to a small number of firms. For the Retail Non-Purpose loan portfolio, balances are higher and more widespread, but limited available historical loss information is available, making it challenging to fit a regression model. The straightforward process for assigning net charge-off rates using the scalar models aligns with the stress testing principle of simplicity. It also ensures that balances across all firms are treated consistently, in line with the stress testing principles.

The Board uses multiple methodologies to calibrate the net charge-off rates applied by the scalar models. These methodology differences are justified by differences in available historical loss data. The net charge-off rates for the International Other Consumer loan, International First Mortgage, International Home Equity loan, and International Small Business loan portfolios are assigned loss rates associated with a percentile of the historical distribution of net charge-off rates. The net charge-off rates for the International Auto loan portfolio are equal to a constant based on the historical net charge-off rates this portfolio has experienced under stress. Finally, the net charge-off rates for the Retail Non-Purpose loan portfolio are equivalent to that of loans for purchasing and carrying securities (as reported on FR Y-14Q, Schedule M.1, Line Item 5.c, referred to in the schedule as “securities lending;” see Section A.d.2 of the Corporate Model Description for more information on the treatment of loans for purchasing and carrying securities, or “margin loans”).[586] In all cases, within each portfolio, identical loss rates are assigned to all balances in the portfolio, regardless of other portfolio characteristics. The exact methodology used to calibrate the scalar models, as well as the loss rates assigned to each portfolio, are available in Section G.ii.a.(3).

(2) Data Used for Modeling

The Board uses historical regulatory reporting data, as well as macroeconomic variables, for the Other Retail models. This section discusses the data used to calibrate the models and project loss rates based on these calibrated models. A more complete explanation of the details of adjustments applied to reported data is available in Section G.ii.c.

Data Used to Calibrate Model Parameters

For most portfolios, the Board collects data for each portfolio at the segment level in the FR Y-14Q, Schedule A (Retail), which defines segments based on loan characteristics. However, other schedules are also relevant. The full list of data sources by portfolio is available in Table G3.

Table G3 - Data Sources for Model Calibration, by Portfolio

Portfolio	**Data Source**
Domestic Small Business loans	FR Y-14Q, Schedule A.9 (U.S. Small Business)
Domestic Other Consumer loans	FR Y-14Q, Schedule A.7 (U.S. Other Consumer)
Student loans	FR Y-14Q, Schedule A.10 (Student Loan)
Domestic Small Business and Corporate Credit Cards	FR Y-14M, Schedule D.1 (Credit Cards)
Retail Non-Purpose loans	N/A

[586] The Board has separately proposed updates to the FR Y-9C instructions that would cause all margin loans from holding companies with at least $5 billion in total assets to be broken out on FR Y-9C, Schedule HC-C, Line 9.b.(1). *See* 89 FR 80244 (October 2, 2024). If these changes are implemented as proposed, the balances reported in FR Y-14Q, Schedule M.1, Line Item 5.c would expand to encompass certain non-purpose lending (note that in addition to retail non-purpose loans, firms hold balances of wholesale non-purpose loans), and the Board’s proposed methodology and projected loss rate described in this section would apply to all balances that are reported as retail non-purpose loans (reported on FR Y-14Q, Schedule M.1, Line Item 4.c) following the implementation of the change.

Portfolio	Data Source
International Other Consumer loans	FR Y-14Q, Schedule A.6 (International Other Consumer)
International Bank and Charge Cards	FR Y-14Q, Schedule A.3 (International Credit Card)
International First Mortgages	FR Y-14Q, Schedule A.5 (International First Mortgage)
International Home Equity loans	FR Y-14Q, Schedule A.4 (International Home Equity)
International Small Business loans	FR Y-14Q, Schedule A.8 (International Small Business)
International Small Business and Corporate Credit Cards	FR Y-14Q, Schedule A.3 (International Credit Card)
International Auto loans and leases	FR Y-14Q, Schedule A.1 (International Auto Loan)

In certain cases, the FR Y-14Q schedules do not exactly align with the Other Retail portfolios, as described below:

- The Small Business and Corporate Credit Card portfolio was historically (through the first quarter of 2012) reported on a since-retired schedule on the FR Y-14Q. Data starting in June 2012 is collected at the loan-level on FR Y-14M, Schedule D, along with other domestic credit card loans.[587] As described later in this section, the Board aggregates the loan-level small business and corporate card data reported on this schedule to align with the segments historically reported on the FR Y-14Q.
- The International Bank and Charge Card portfolio and the International Small Business and Corporate Card portfolio share a schedule within FR Y-14Q, Schedule A (Retail).
- Segment-level data are not collected for the Retail Non-Purpose Loan portfolio.

[587] Small-business and corporate credit card portfolio data, previously collected in the FR Y-14Q, are now collected at the loan level on the FR Y-14M, Schedule D, Domestic Credit Card Collection (D.1 – Loan Level Table) and are subsequently aggregated to the segment level.

All covered firms with material portfolios are required to report the relevant FR Y-14 Schedules.[588] New reporters are required to submit historical data according to the requirements in the instructions.[589]

The data from the FR Y-14Q and FR Y-14M schedules listed above are used to calibrate the model parameters. Historical data are available beginning in the first quarter of 2007, although the amount of data available in practice varies by portfolio, based on the number of firms in each portfolio that are material. The Other Retail models rely on data from the beginning of the historical data in the first quarter of 2007 through the end of 2019 to calibrate the model parameters. By ending the sample period in 2019, the models are not impacted by the distortions of the COVID-19 pandemic, during which there were sharp swings in unemployment rate despite net charge-off rates remaining stable. A detailed discussion of the costs and benefits of including data from during and after 2020 in the estimation sample is available in Section G.iii.a.

The schedules are reported at a monthly frequency; in each quarter, firms report separate entries for each month of data within the quarter. For each FR Y-14Q schedule, each firm reports data divided into different categories, referred to in the instructions as “segment variables.” For instance, in FR Y-14Q, Schedule A.7 (U.S. Other Consumer), segment variables include Product Type, Delinquency Status, Original Credit Score, and Original LTV.[590] For each of these pairwise categories (for instance, where Product Type is “Secured – Revolving,” Delinquency

[588] FR Y-14Q Instructions, at 1–2. For firms subject to category IV standards, material portfolios are defined as those with asset balances greater than $5 billion or with asset balances greater than ten percent of Tier 1 capital on average for the four quarters preceding the reporting period. For firms subject to category I, II, or III standards, material portfolios are defined as those with asset balances greater than $5 billion or asset balances greater than five percent of Tier 1 capital on average for the four quarters preceding the reporting period. Id. at 2. *See also* FR Y-14M Instructions, at 4.
[589] *See* FR Y-14Q Instructions, at 8.
[590] FR Y-14Q Instructions, at 38-39.

Status is “Current and 1-29 days past due,” Original Credit Score is “>620 FICO® or equivalent,” and Original LTV is “>=100”), a large number of summary statistics are available, including total balance outstanding, number of accounts, balance of new originations, gross charge-offs, and recoveries.

For the Domestic Small Business and Corporate Credit Cards portfolio, for the period where data are reported on FR Y-14M, Schedule D (Credit Cards), the loan-level data are aggregated such that they recreate the “segment variables” and summary statistics on FR Y-14Q schedules. The process for aggregating the loan-level data is described in Section G.2.c.

In certain cases, erroneous or outlier data are excluded from the estimation sample. The process for setting these exclusions is detailed in Section G.ii.c. Aside from these cases, all reported data are used to estimate the model, including data reported historically by firms that no longer report a given schedule. Using all reported data maximizes the data available to fit the model, while ensuring results are not affected by the subset of firms reporting at any given point in time.

In addition to historical portfolio data, macroeconomic data are included as well in the regression models to account for the historical differences in net charge-off rates that occur in different macroeconomic environments. These macroeconomic variables vary by portfolio; the macroeconomic variables used in each equation are detailed in Section G.ii.a.(3).

Data Used to Project Losses

In general, the data used to project losses is analogous to the data used to calibrate the model parameters. Firm data is reported on the schedules listed in Table G3, while macroeconomic variables are sourced from the supervisory stress test scenarios.

In addition to the data the models use to assign loss rates, balances reported on FR Y-14Q, Schedule M.1 (Balances) are compiled by the balance sheet line-item projections calculator.[591] The line items from FR Y-14Q, Schedule M.1 (Balances) associated with each portfolio are shown in Table G4.[592] The loss rates projected by the models are applied to these balances to produce estimates of loan losses and provisions on each of the Other Retail portfolios.

Table G4 - FR Y-14Q, Schedule M.1 (Balances) Fields, by Portfolio

Portfolio	**FR Y-14Q, Schedule M.1 (Balances) Field(s)**
Domestic Small Business loans	Line Item 2.b, Column A (CALBP368)
Domestic Other Consumer loans	Line Items 4e and 4f, Column A (CALBR679, CALBR683)
Student loans	Line Item 4b, Columns A and C (CALBR667, CALBR669)
Domestic Small Business and Corporate Credit Cards	Line Item 2c, Column A (CALBP880)
Retail Non-Purpose loans	Line Item 4c, Columns A and C (CALBR671, CALBR673)
International Other Consumer loans	Line Items 4e and 4f, Column C (CALBR681, CALBR685)
International Bank and Charge Cards	Line Items 3a and 3b, Column C (CALBR657, CALBR661)
International First Mortgages	Line Items 1a and 1b, Column C (CALBP330, CALBP334)
International Home Equity loans	Line Items 2a and 2b, Column C (CALBP338, CALBP342)
International Small Business loans	Line Item 2b, Column C (CALBP837)
International Small Business and Corporate Credit Cards	Line Item 2b, Column C (CALBP883)
International Auto loans and leases	Line Items 4a and 4d, Column C (CALBR665, CALBR677)

591 *See* Section A of the Aggregation Models Description (Balances Model).
592 Micro Data Reference Manual (MDRM) codes are shown in parentheses. *See* "Micro Data Reference Manual," Board of Governors of the Federal Reserve System, https://www.federalreserve.gov/apps/mdrm/ for more information.

(3) Estimation of Model Parameters

Estimation of Regression Models

This section describes the process of using the data described above to fit the models described in this model description.

First, the reported data are aggregated to the segment and quarter level for each firm. There are two components of this approach. First, monthly data reported for each portfolio as in Table G3 are aggregated to quarterly data for each firm and segment. To aggregate the monthly data to quarterly, the models first calculate the quarterly net charge-off rate for each portfolio and the quarterly delinquency rate (defined as the share of loans 60 or more days past due) for the portfolios that comprise the International Cards Model. To calculate the quarterly net charge-off rate, denoted by $NCO_{i,k,t}$ in Equations G1 and G3, the following formula reproduced in Equation G4 is used:

Equation G4 – Definition of Net Charge-off Rate

$$NCO_{i,k,t} = \frac{OS_{i,k,t}^{NCO}}{OS_{i,k,t}}$$

where *i* represents the firm (of *N* total covered firms); *k* represents a segment of loans within the portfolio (of *K* total segments); *t* represents time in quarters (of *T* total quarters); *NCO* denotes the net charge-off rate; OS^{NCO} represents the sum of the net dollar amount of outstanding balances that was charged off over the three months of the quarter; and *OS* represents the total outstanding principal balance in the last month of the quarter.[593]

[593] In most portfolios, NCO takes the value of the variable "$ Net Charge-offs" reported on the FR Y-14Q, Schedule A (Retail), while OS takes the value of the variable "$ Outstandings." For the Small Business and Corporate Credit Card Portfolio data reported on the FR Y-14M, Schedule D, Domestic Credit Card Collection (D.1 – Loan Level Table) (beginning in June 2012), net charge-offs are defined as the gross charge-offs net of recoveries, where gross charge-offs are the sum of "gross charge-off amount in current month" (Line Item 62) and recoveries are defined as

Similarly, the quarterly share of loans that are at least 60 days past due, denoted by $DEL(60+)_{i,k,t}$ in Equation G3, is computed as the total outstanding balances on loans that are 60-89 days past due ($OS_{i,k,t}^{60-89DPD}$), 90-119 days past due ($OS_{i,k,t}^{90-119DPD}$), and 120 or more days past due ($OS_{i,k,t}^{120+DPD}$) divided by the total outstanding balances in the last month of the quarter ($OS_{i,k,t}$). This is shown mathematically in Equation G5:

Equation G5 – Definition of Delinquency Rate

$$DEL(60+)_{i,k,t} = \frac{OS_{i,k,t}^{60-89DPD} + OS_{i,k,t}^{90-119DPD} + OS_{i,k,t}^{120+DPD}}{OS_{i,k,t}}$$

where *i* represents the firm (of *N* total covered firms); *k* represents a segment of loans within the portfolio (of *K* total segments); *t* represents time in quarters (of *T* total quarters). Loans are identified as 60-89 days past due, 90-119 days past due, and 120 or more days past due based on the "Delinquency status" variable reported on FR Y-14Q, Schedule A.3 (International Credit Card).

Second, as noted previously, the FR Y-14Q schedules (or in the case of the Small Business and Corporate Credit Card portfolio, the aggregation of the loan-level data as described) include a large number of segments reported for each firm in each portfolio.[594] For use in the models, the disaggregated segments reported by each firm are aggregated to the smaller number of segments defined in the model and listed further in Table G5**Table G5** . The segmentation for each portfolio is chosen based on the most important determinants of net

the sum of sum of "recovery amount in current month" (Line Item 63) for all accounts in a segment reported in a given month where charge-offs are reported (Line Item 61; a charge-off is reported if this line item is not blank). The outstanding balance for the Small Business and Corporate Credit Card Portfolio is defined as the sum of the "cycle ending balance" (Line Item 15) for all accounts in a segment reported in a given month, or in the case when cycle ending balance is unavailable, "month ending balance" (Line Item 122) is substituted. For the student loan portfolio reported on FR Y-14Q, Schedule A.10, only balances in repayment ("$ Outstandings in repayment") are included in the balance. Further data adjustments are described in Section G.ii.c.

[594] FR Y-14Q, Schedule A (Retail) contains data for each portfolio at the firm level for hundreds of segments. The exact segments are available in the FR Y-14Q instructions.

charge-off rates within a relevant portfolio. In certain cases, limitations of the data available on historical reporting forms prevent the effective use of certain variables in modeling; for instance, even though credit score categories are reported on each of the FR Y-14Q sub-schedules, in many cases the buckets are not granular enough to differentiate the riskiness of loans, limiting their usefulness in modeling. While it would be possible to update the reporting forms going forward to capture more granular definitions of credit scores, without sufficient historical data, the model parameters cannot be calibrated. Additionally, modeling a small number of segments is preferable as it reduces the impact of outliers through more aggressive aggregation, helping to avoid spurious coefficients that do not reflect the true relationship between a reported variable and credit risk. Based on these factors, the segmentation chosen by the Board is shown in Table G5.

Specifically for the Student Loan Model, only a portion of the loans reported on FR Y-14Q, Schedule A.10 (Student Loan) are incorporated into the regression model framework. The Student Loan portfolio includes private student loans as well as government guaranteed student loans, such as loans originated under the Federal Family Education Loan Program (FFELP).[595] Because FFELP loans receive a 97 percent or higher government guarantee,[596] depending on the origination date, losses on government guaranteed loans are expected to be small. However, the guarantee is often not 100 percent, and lenders are responsible for a small portion of losses on defaulted accounts. To account for this guarantee, the Student Loan Model uses a regression

[595] The FFELP was replaced in 2010; federal student loans originated after this program's end date were originated directly by the U.S. Department of Education. However, small balances of legacy FFELP loans remain on firm balance sheets.
[596] For more information, *see* "Comptrollers Handbook: Safety and Soundness – Student Lending," OCC. 3–4, 6 (Version 1.3, Dec. 27, 2018), https://www.occ.gov/publications-and-resources/publications/comptrollers-handbook/files/student-lending/pub-ch-student-lending.pdf.

framework only for private student loans; government guaranteed loans are instead assigned a fixed, scalar loss rate.

Because new government guaranteed loans have not been originated since 2010, and most of the legacy balance of FFELP loans has paid off, government guaranteed loans account for a small portion of total student loan balances reported on the FR Y-14Q report. Furthermore, because new loans are not originated, the loans that remain in the portfolio exhibit survivorship bias, as they are by construction the subset of loans that have not yet been fully repaid. This survivorship bias makes it challenging to use historical behavior on government guaranteed student loans to assess the probability that the remaining government guaranteed loans will default in the future. Furthermore, given the time that has passed since government guaranteed student loans have been originated, the remaining balances on government guaranteed student loans are sufficiently immaterial that changes to the government guaranteed student loan loss rate would not materially impact any firm's stress losses. Because of (1) the unique challenges of calibrating losses on a portfolio for which loans have not been originated in 15 years and (2) the immateriality of the portfolio, the Board relies on analysis described below for assigning loss projections for government guaranteed student loans. In particular, given the lack of new originations and the challenges described above for modeling such a portfolio, as well as the small balances remaining in the portfolio, the Board determined that it is not appropriate to continually recalibrate the projections for losses on government guaranteed student loans.

To calibrate the fixed, scalar loss rate for government student loans, the Board separately projects the probability of default of government student loans and the loss given default for these loans. The probability of default is calculated based on the share of loans that are 120 or more days past due in a given period (as reported on FR Y-14Q, Schedule A.10, Field A.4); the model uses a threshold of 120 or more days past due for determining default as this is the most severe delinquency category reported in this field. This threshold of 120 or more days past due is more conservative than the default definition used by the Department of Education, which defines a loan as in default when no payment has been made in 270 days.[597] However, due to the limited granularity available on FR Y-14Q, Schedule A.10 and the limited balances in the portfolio causing sparse segments, the Board uses a 120-day threshold. The projected quarterly net charge-off rate for government student loan balances is the product of the probability of default and the loss given default on these balances; the process for calibrating the probability of default and loss given default for government guaranteed student loans is described below:

- The probability of default for government guaranteed student loans is assumed to be 4.5 percent per quarter. This probability of default is calibrated based on historical analysis of the FR Y-14Q data for private student loans. Private student loans were used for this analysis in line with the stress testing principle of simplicity, as the Board assessed historical default rates when developing the private student loan regression model. In particular, the Board used the monthly FR Y-14Q data for private student loans from 2007 through 2011 to project the share of total balances in default, during a hypothetical recession, and determined that this share of balances in default (120 or more days past due) was approximately 1.5 percent per month. The Board assumes that a new cohort of loans defaults in each month, rather than loans remaining in default for multiple months. This yields a quarterly default rate of 4.5 percent per quarter. While it is conservative to assume that a new cohort of loans will default in each month—rather than a loan remaining in default for multiple periods—this is balanced by the fact that the defaulted share is calibrated based on private student loans, which have substantially lower default rates than government guaranteed student loans. In all periods in the historical FR Y-14Q data, default rates on government guaranteed student loans were at least five times greater than that of private student loans; since 2010, default rates on government guaranteed student loans have been at least ten times greater than that of private student loans. Furthermore, in recent years, default rates for government guaranteed student loan balances reported in the FR Y-14Q are substantially higher than 1.5 percent, exceeding 4 percent consistently and reaching 10 percent or higher in some periods.
- The loss given default for government student loans is assumed to be 3 percent. This is based on the fact that 97 percent is the minimum guarantee rate for FFELP loans, as described above.

[597] *See* "Default." Federal Student Aid, U.S. Department of Education, https://studentaid.gov/help-center/answers/article/default.

Based on these projections of probability of default and loss given default, the Board projects the net charge-off rate for government guaranteed student loans to be 0.135 percent per quarter. While this net charge-off rate is higher than historical rates observed during the 2008 financial crisis period, it is consistent with the stress testing principle of conservatism. Throughout the rest of this document, the regression model applied to the Student Loan Model is often referred to as the "Private Student Loan Model" or "Private Student Loan Equation."

Subject to the above caveat about government guaranteed student loans, the segmentation used for the portfolios with regression models is available in Table G5.

Table G5 - Segmentation Used in Modeling, by Portfolio

Model Type	Portfolio	Segmentation
Domestic	Domestic Small Business loans	Segmentation by product type secured unsecured
	Domestic Other Consumer loans	Segmentation by product type secured unsecured
	Student loans[598]	Segmentation by credit score > 660 FICO® or equivalent <= 660 FICO® or equivalent credit score missing
	Domestic Small Business and corporate credit card loans	Segmentation by product type small business card corporate card
International	International Bank and Charge Cards and International Small Business and Corporate Credit Cards	Segmentation by portfolio and primary borrower residency, for a total of eight segments Portfolio segments International Bank and Charge Cards International Small Business and Corporate Credit Cards Primary borrower residency segments Canada Europe, Middle East, and Africa (EMEA)

598 The regression model only covers private student loans. Government guaranteed student loans are instead assigned a scalar loss rate.

Model Type	Portfolio	Segmentation
		Latin America and Caribbean (LATAM) Asia Pacific (APAC)

Next, macroeconomic data in each quarter are merged with the portfolio data. The domestic model, described in Equation G1, relies on transformations of the U.S. unemployment rate[599] to account for the impacts of macroeconomic stress.[600] The Board tested the inclusion of other macroeconomic variables—such as disposable personal income growth, that could affect a borrower's ability to repay—but determined that using the U.S. unemployment rate made the models sufficiently sensitive to the macroeconomic environment while minimizing the complexity of the model. For the International Model, the change in the U.S. unemployment rate[601] is used as an indicator of global stress, while the Euro Area Unemployment rate,[602] U.S. real GDP growth rate,[603] Mexico real GDP growth rate,[604] and Developing Asia real GDP growth[605] are used to measure regional economic conditions in the Europe, Middle East, and Africa (EMEA), Canada, Latin America and Caribbean (LATAM), and Asia Pacific (APAC) regions, respectively. See Section G.ii.b.(1) for further discussion of the modeling decisions surrounding macroeconomic variables.

With the data prepared, the equations are estimated. Each of the models described in Equations G1, G2, and G3 are estimated using weighted-least squares (WLS), using firm by

[599] Sourced from the Bureau of Labor Statistics.
[600] Each of the Domestic Models uses the quarterly change in the U.S. unemployment rate (with exact transformations varying by portfolio). The Student Loan model additionally includes the level of the U.S. unemployment rate.
[601] Data sourced from the Bureau of Labor Statistics.
[602] Data sourced from the Statistical Office of the European Communities.
[603] Data sourced from the Bureau of Economic Analysis.
[604] Data sourced from National Institute of Statistics and Geography of Mexico.
[605] The Developing Asia Real GDP growth rate is the weighted average GDP growth rate of China, India, South Korea, Hong Kong Special Administrative Region, and Taiwan, weighted by the nominal GDP of these places. This group of countries was chosen to broadly capture economic conditions of this region. Data are sourced from Bank of Korea; National Bureau of Statistics of China; Indian Central Statistics Office; Census and Statistics Department of Hong Kong; and Taiwan Directorate-General of Budget, Accounting and Statistics.

segment balances as the weights. The weighted-least squares approach recognizes that the historical net charge-off rates among smaller segments are less trustworthy and more subject to outliers. Using weighted-least squares prevents these less trustworthy smaller segments, which have much more volatile reported net charge-off rates, from unduly influencing the model estimates.

As previously discussed, the Domestic Models presented in Equation G1 are estimated separately for each of the four Domestic portfolios. Results are shown in Table G6. Each column represents the model for one of the Domestic portfolios, as labeled, while each row represents a variable used in the model. For each row-column pair, the first number represents the coefficient, and the second number, in parentheses, represents the standard error. At the bottom of each equation, the R-squared of the equation is shown.[606] Descriptions of each of the variables are available below the table.

[606] Formally, the R-squared values reported in this table represent the R-squared of an equivalent model estimated with a constant intercept term in place of one of the segment variables. This equation is mathematically equivalent to the version shown in the table.

Table G6 - Model Coefficients for Domestic Portfolios

	$NCO_{i,k,t}$ rate for domestic portfolios			
	Other Consumer	Small Business Loan	Small Business and Corporate Credit Card	Private Student
Net Charge-Off Rate in Previous Quarter	0.9379	0.9064	0.8975	0.8229
	(0.007)	(0.010)	(0.009)	(0.016)
Macro Variables				
Level of Unemployment Rate	--	--	--	0.0003
	--	--	--	(0.000)
Quarterly Change in Unemployment Rate	0.0018	0.0021	--	0.0019
	(0.000)	(0.000)	--	(0.000)
Quarterly Change in Unemployment Rate in Previous Quarter	0.0014	0.0010	0.0042	--
	(0.000)	(0.000)	(0.000)	--
Risk Segment				
Secured	0.0002	0.0004	--	--
	(0.000)	(0.000)	--	--
Unsecured	0.0011	0.0010	--	--
	(0.000)	(0.000)	--	--
Corporate Credit Card	--	--	0.0005	--
	--	--	(0.000)	--
Small Business Card	--	--	0.0014	--
	--	--	(0.000)	--
Subprime (FICO® Less than or Equal to 660 or Equivalent)	--	--	--	0.0004
	--	--	--	(0.001)
Non-Subprime (FICO® Greater than 660 or Equivalent)	--	--	--	-0.0021
	--	--	--	(0.000)
Credit score unavailable	--	--	--	-0.0019
	--	--	--	(0.000)
Seasonality Variables				
Quarter 2	--	--	--	0.0025
	--	--	--	(0.000)
Quarter 3	--	--	--	0.0010
	--	--	--	(0.000)
Quarter 4	--	--	--	0.0025
	--	--	--	(0.000)
R^2	0.94	0.91	0.96	0.84

A description of each of the variables in Table G6 and its interpretation is below. Further discussion of the variables included in each of the models is available in Section G.ii.b.(1):

- "Net Charge-off Rate in the Previous Quarter" is the previous value of the net charge-off rate for a given firm in a given segment. The coefficient is relatively large, suggesting that net charge-off rates are persistent. This means that a firm that has a relatively high or low net charge-off rate in a given segment in a given quarter can be expected to have a high or low (respectively) net charge-off rate in the next quarter. This term captures the different features that make certain firm's loans more or less risky that are not able to be captured by other variables in the model.
- The "Level of Unemployment Rate" is the U.S. unemployment rate in a given quarter. In three of the four Domestic portfolios, the level of the unemployment rate tends to be less of a factor for predicting net charge-off rates than the change in the unemployment rate (see next bullet). However, in the Private Student Loan equation, the level of unemployment rate is included in addition to the change in unemployment rate, based on the historical correlation between the unemployment level and student loan loss rates during the 2008 financial crisis period. In particular, net charge-off rates are higher during periods when the unemployment rate is higher. The importance of the level of unemployment rate is specific to the Student Loan portfolio as the level of unemployment rate captures the job market conditions that directly impact the income prospects of new graduates with student loans. In contrast, the remaining Domestic portfolios generally involve borrowers with more stable income, so the level of unemployment rate is less relevant.
- The "Quarterly Change in Unemployment Rate" is the difference between the current unemployment rate and the unemployment rate in the previous quarter. The "Quarterly Change in Unemployment Rate in the Previous Quarter" is the difference between the previous quarter's unemployment rate and the unemployment rate from two quarters ago. Each of these terms is used to measure deterioration in the labor market, which is associated with higher net charge-off rates. The quarterly change in the previous quarter %is used to reflect that often there is a lag between when borrowers experience job loss and when the loan charges off, as borrowers deplete their savings and then progress through delinquency. Between these two variables, the Board includes one or both, chosen separately by portfolio, based on statistical fit; in particular, the Board tested multiple specifications before choosing the one that most accurately projected historical net charge-off rates. The determinations are as follows:
    - Other Consumer: Both the Quarterly Change in Unemployment Rate and the Quarterly Change in Unemployment Rate in the Previous Quarter are used.
    - Small Business Loan: Both the Quarterly Change in Unemployment Rate and the Quarterly Change in Unemployment Rate in the Previous Quarter are used.
    - Small Business and Corporate Credit Card: Only the Quarterly Change in Unemployment Rate in the Previous Quarter is used.
    - Private Student Loan: Only the Quarterly Change in Unemployment Rate is used, in addition to the level of unemployment rate.

- The “Risk Segment” variables align with the segments described in Table G5. In the Other Consumer and Small Business Loan Models, the lower coefficient on secured loans compared to unsecured loans indicates that secured loans have lower net charge-offs than unsecured loans, reflecting the higher risk associated with unsecured lending. In the Small Business and Corporate Credit Card Model, the coefficient on Corporate Credit Cards is lower than that of Small Business Cards, reflecting that historically corporate credit cards have lower net charge-off rates than small business cards. Finally, in the Private Student Loan equation, subprime loans have the highest coefficient, followed by loans with missing credit scores, reflecting the expected level of risk for borrowers with different levels of creditworthiness.
- The “Seasonality” variables measure the expected difference in net charge-off rate for balances in a given calendar quarter (Quarter 2, for April-June; Quarter 3, for July-September; Quarter 4, for October-December), compared to equivalent balances in the first calendar quarter (January-March, or “Q1”). This is only included in the Private Student Loan equation, as the other portfolios do not show empirically relevant seasonality in the historical data. The positive coefficients on all quarters indicate persistently higher historical net charge-off rates based in these quarters compared to Q1. The seasonality observed for student loans is likely reflective of the calendar-based nature of the product, as many borrowers finish school and enter repayment (and in some cases, delinquency) at similar points in the calendar year.

For the International Model defined in Equations G2 and G3, the model consists of two equations, each of which is applied to both the International Bank and Charge Card and International Small Business and Corporate Card Portfolios.

Recall that the International Model (Equations G2 and G3) is estimated once using the data of both international cards portfolios. Results are shown in Table G7. Each column represents one of the two equations, as labeled, while each row represents a variable used in the model. For each row-column pair, the first number represents the coefficient, and the second number represents the standard error. At the bottom of each equation, the R-squared of the equation is shown.[607]

[607] Similar to the Domestic Models, formally, the R^2 values reported in this table represent the R^2 of an equivalent model estimated with a constant intercept term in place of one of the segment variables. This equation is mathematically equivalent to the version shown in the table.

In some cases, macroeconomic variables in the International Model enter by region. This means that the models are specified such that changes in region-specific macroeconomic variables impact only the balances in those regions, and allows the model to capture regional differences in the macroeconomic environment. In addition to regional conditions, the model also uses macroeconomic factors that apply to balances across regions, to reflect the impacts of the global macroeconomic environment. Descriptions of each of the variables used in the model are available below the table.

Table G7 - Model Coefficients for International Cards Portfolios

	$\boldsymbol{DEL(60+)_{i,k,t}}$	$\boldsymbol{NCO_{i,k,t}}$**rate**
Net Charge-off Rate in Previous Quarter	-- --	0.3582 (0.0264)
Delinquency Rate (60 or more Days Past Due) in Previous Quarter	0.9396 (0.0090)	0.2906 (0.0155)
Flag for International Bank and Charge Cards in Canada Region	0.0013 (0.0004)	0.0014 (0.0004)
Flag for International Bank and Charge Cards in EMEA Region	0.0008 (0.0003)	-0.0006 (0.0004)
Flag for International Bank and Charge Cards in LATAM Region	0.0027 (0.0005)	0.0030 (0.0001)
Flag for International Bank and Charge Cards in APAC Region	0.0019 (0.0005)	-0.0002 (0.0001)
Flag for International SME Cards	0.0017 (0.0003)	-0.0006 (0.0004)
Proportion of International Bank and Charge Cards with FICO® <= 620 or Equivalent	0.0042 (0.0011)	-- --
Proportion of International Bank and Charge Cards with FICO® > 620 or Equivalent	0.0001 (0.0003)	-- --
U.S. Unemployment Rate Quarterly Change in the Previous Quarter	0.0014 (0.0003)	-- --
U.S. Unemployment Rate Quarterly Change in the Previous Quarter, for Balances not in EMEA Region	-- --	0.0019 (0.0004)
Euro Area unemployment rate Quarterly Change Two Quarters Prior, for Balances in EMEA Region	-- --	0.0026 (0.0001)

	$DEL(60+)_{i,k,t}$	$NCO_{i,k,t}$ rate
U.S. Real GDP Growth, for Balances in Canada Region	-0.0003 (0.0001)	-- --
Quarterly Change in the Euro Area unemployment rate, for Balances in EMEA Region	0.0036 (0.0006)	-- --
Mexico Real GDP Growth Rate, for Balances in LATAM Region	-0.0003 (0.0001)	-- --
Mexico Real GDP Growth Rate in the Previous Quarter, for Balances in LATAM Region	-0.0002 (0.0001)	-- --
Developing Asia Real GDP Growth, for Balances in APAC Region	-0.0002 (0.0001)	-- --
R^2	0.97	0.85

A description of each of the variables in Table G7 and its interpretation is below. Further discussion of the variables included in each of the models is available in Section G.ii.b.(1):

- Net Charge-off Rate in Previous Quarter: In the net charge-off equation, similar to the Domestic Models, a higher net charge-off rate in the previous quarter is indicative of a higher net charge-off rate in the current quarter, indicating persistence. Because of the inclusion of the delinquency equation, which provides a second measure of firm-specific variation, the coefficient on previous quarter net charge-off rate is smaller than that of the Domestic Models.
- Delinquency Rate (60 or more Days Past Due) in Previous Quarter: A higher delinquency rate in the previous quarter is associated with a higher delinquency rate in the current quarter, as well as higher net charge-off rates in the current quarter. This is expected, as higher delinquency rates are persistent based on the unique and unobserved characteristics of each portfolio, while net charge-offs often come from the population of loans that were delinquent in the previous quarter.
- Flag for International Bank and Charge Cards in Canada Region: This variable is set to 1 for International Bank and Charge Card exposures in Canada, and 0 for all other loans (meaning International Bank and Charge Cards in other regions, as well as all International Small Business and Corporate Cards). This variable is included based on the expectation that International Bank and Charge Cards will have persistent differences in delinquency and net charge-off rates compared to International Small Business and Corporate Cards, and that there will be persistent differences in delinquency and net charge-off rates across regions.
- Flag for International Bank and Charge Cards in EMEA Region: This variable is set to 1 for International Bank and Charge Card exposures in Europe, the Middle East, and Africa, and 0 for all other loans (meaning International Bank and Charge Cards in other regions, as well as all International Small Business and Corporate Cards). This variable is included based on the expectation that International Bank and Charge Cards will have persistent differences in delinquency and net charge-off rates compared to International

Small Business and Corporate Cards, and that there will be persistent differences in delinquency and net charge-off rates across regions.

- Flag for International Bank and Charge Cards in LATAM Region: This variable is set to 1 for International Bank and Charge Card exposures in Latin America and the Caribbean, and 0 for all other loans (meaning International Bank and Charge Cards in other regions, as well as all International Small Business and Corporate Cards). This variable is included based on the expectation that International Bank and Charge Cards will have persistent differences in delinquency and net charge-off rates compared to International Small Business and Corporate Cards, and that there will be persistent differences in delinquency and net charge-off rates across regions.
- Flag for International Bank and Charge Cards in APAC Region: This variable is set to 1 for International Bank and Charge Card exposures in the Asia-Pacific Region, and 0 for all other loans (meaning International Bank and Charge Cards in other regions, as well as all International Small Business and Corporate Cards). This variable is included based on the expectation that International Bank and Charge Cards will have persistent differences in delinquency and net charge-off rates compared to International Small Business and Corporate Cards, and that there will be persistent differences in delinquency and net charge-off rates across regions.
- Flag for International Small Business and Corporate Cards: This variable is set to 1 for International Small Business and Corporate Card exposures, and 0 for International Bank and Charge Card exposures. This variable is included based on the expectation that International Bank and Charge Cards will have persistent differences in delinquency and net charge-off rates compared to International Small Business and Corporate Cards. Because of the sparser International Small Business and Corporate Card portfolio, differences across region are not considered. The Board determined that due to sparser data, regional specific variation would not be precisely estimated.
- Proportion of International Bank and Charge Cards with FICO® <= 620 or Equivalent: This variable is set equal to the share of International Bank and Charge Card balances for a given firm in a given geographic region in a given period with reported credit scores of less than or equal to 620 FICO® or equivalent and is used to compare the projected net charge-off rate for these balances compared to that of International Bank and Charge Cards with unavailable credit scores. This variable takes into account that a larger share of subprime balances is associated with higher delinquency rates. This variable is only applied for International Bank and Charge Cards; since business-purpose Small Business and Corporate Cards are less reliant on credit scoring, credit score is not considered for these cards. Additionally, the Board determined based on analysis of historical data that credit scores were a strong indicator of delinquency but a less strong indicator of net charge-offs, so this variable is used only in the delinquency equation.
- Proportion of International Bank and Charge Cards with FICO® > 620 or Equivalent: This variable is set equal to the share of International Bank and Charge Card balances for a given firm in a given geographic region in a given period with reported credit scores of greater than 620 FICO® or equivalent, and is used to compare the projected net charge-off rate for these balances compared to that of International Bank and Charge Cards with unavailable credit scores. In practice, these rates are very similar, reflecting that many borrowers with missing credit scores are likely strong borrowers in regions that don’t use individual credit scores. This variable is only applied for International Bank and Charge

Cards; since business-purpose Small Business and Corporate Cards are less reliant on credit scoring, credit score is not considered for these cards. Additionally, the Board determined based on analysis of historical data that credit scores were a strong indicator of delinquency but a less strong indicator of net charge-offs, so this variable is used only in the delinquency equation.

- U.S. Unemployment Rate Quarterly Change in the Previous Quarter: This is the difference between the U.S. unemployment rate in the previous quarter compared to the unemployment rate two quarters ago. In the delinquency equation, the U.S. unemployment rate is used as a measure of global economic conditions, with weaker global conditions associated with higher delinquency. The previous quarter's value is used to reflect that time may elapse between when global conditions deteriorate and when they show up in delinquency rates; this value was chosen compared to the change in the current quarter based on the testing of multiple potential specifications.
- U.S. Unemployment Rate Quarterly Change in the Previous Quarter, for Balances not in EMEA Region: This is the difference between the U.S. unemployment rate in the current quarter compared to the unemployment rate in the previous quarter for balances not in the EMEA Region; for balances in the EMEA region, it is set to zero. In the net charge-off equation, the U.S. unemployment rate is used as a measure of global economic conditions, with weaker global conditions associated with higher delinquency. This value, compared to changes in unemployment rate in previous quarters, was chosen compared to the change in the current quarter after testing multiple potential specifications. For balances in the EMEA region, Board analysis determined that the net charge-off rate was less affected by changes in the U.S. unemployment rate compared to other regions, especially when the Euro Area unemployment rate (see below) is included. Therefore, this variable is not applied to balances in the EMEA region.
- Euro Area unemployment rate Quarterly Change Two Quarters Prior, for Balances in EMEA Region: This is the difference between the Euro Area unemployment rate two quarters prior compared to the Euro Area unemployment rate three quarters prior for balances in the EMEA Region; for other balances, it is set to zero. In the net charge-off equation, it was determined that historical values of this variable are more predictive of historical net charge-off rates in the EMEA region, compared to a specification relying on U.S. unemployment rates. Using the value from two quarters prior, as opposed to more contemporaneous values, was chosen compared to the change in the current quarter after testing multiple potential specifications. For balances in the EMEA region, Board analysis determined that the net charge-off rate was less affected by changes in the U.S. unemployment rate compared to other regions, especially when the Euro Area unemployment rate (see below) is included.
- U.S. Real GDP Growth,[608] for Balances in Canada Region; Quarterly Change in the Euro Area unemployment rate, for Balances in EMEA Region; Mexico Real GDP Growth Rate, for Balances in LATAM Region; Mexico Real GDP Growth Rate in the Previous Quarter, for Balances in LATAM Region; Developing Asia Real GDP Growth, for Balances in APAC Region: These variables are used to reflect local economic conditions for each region in the delinquency equation and are applied only to balances in the

[608] All GDP growth rates used are quarterly changes, at an annualized rate.

associated region; balances in other regions are assigned a value of “0” in these fields. Region-specific variables are explained below:

- Canada: The model uses the U.S. Real GDP growth rate. Given the strong historical correlation between U.S. and Canadian economic conditions, the U.S. real GDP growth rate is a reasonable proxy for the Canadian balances. Higher U.S. Real GDP growth is associated with lower net charge-off rates among Canadian balances, as economic theory would suggest.
- EMEA: The model uses the quarterly change in the Euro Area unemployment rate. Analysis of supervisory information indicates that the majority of EMEA balances are in the Euro Area, and the Euro Area unemployment rate is empirically a strong predictor of net charge-off rates for these balances. Higher Euro Area unemployment rate is associated with higher net charge-off rates among EMEA balances, as economic theory would suggest.
- LATAM: The model uses the Mexico Real GDP growth rate and the previous quarter’s value of Mexico Real GDP growth rate. Analysis of supervisory information indicates that virtually all of LATAM balances are in Mexico, and the Mexico Real GDP growth rate is empirically a strong predictor of net charge-off rates for these balances. The previous value as well as the contemporaneous value is used based on assessment of the empirical model fit. Higher Mexico Real GDP growth is associated with lower net charge-off rates among LATAM balances, as economic theory would suggest.
- APAC: The model uses the Developing Asia Real GDP growth rate. This group of countries broadly captures economic conditions of this region. While the relationship is slightly noisy due to the wide range of geographies over which this indicator is estimated, the model coefficients demonstrate that higher Developing Asia Real GDP growth is associated with lower net charge-off rates among APAC balances, as economic theory would suggest.

Estimation of Scalar Models

As described previously, the scalar models assign a single net charge-off rate within each of the six portfolios that utilize a scalar model. This section describes the process for calibrating these net charge-off rates.

The scalars for the international Other Consumer loans, International First Mortgage, International Home Equity loan, and International Small Business loan are calibrated using data as indicated in Table G3. As previously noted, the scalars are calibrated using data from the first quarter of 2007 through the fourth quarter of 2019. The process is as follows. First, net charge-off balances and total balances are aggregated up to the industry level to compute an industrywide net charge-off rate.[609] Next, for each quarter for which data is available, the net charge-off rate in the quarter is added to the net charge-off rate for the eight quarters immediately succeeding, to produce the 9-quarter cumulative loss rate associated with the first quarter in the range.[610] This process yields a quarterly dataset of 9-quarter cumulative loss rates for the period from the first quarter of 2007 through the fourth quarter of 2017, with the fourth quarter of 2017 the last period for which nine quarters of cumulative losses can be produced using data through 2019.

With this dataset prepared, the scalar loss rate is determined based on a percentile of the resulting distribution. For the supervisory severely adverse scenario, the 93rd percentile is used to reflect stressful economic conditions. The use of the 93rd percentile is calibrated based on the frequency of severe recessions in historical data.[611] These scalar loss rates are listed in Table G8.

Unlike the four aforementioned portfolios, there is no available data on historical losses for the International Auto loan and Retail Non-Purpose loan portfolios covering the entirety of a business cycle. For the International Auto loan portfolio, certain historical data are reported on the FR Y-14Q; however, no firm has reported data on the FR Y-14Q, Schedule A.1 (International Auto Loan) since 2013;[612] as a result, historical data does not cover a complete business cycle.

[609] Net charge-off rate is defined as the total dollars of net charge-offs over the three months of a quarter divided by the quarter-end balances, similar to the definition used in the Regression Models. Unlike the Regression Models, net charge-off rates for the Scalar Models are calculated at the industry-, rather than firm-level.
[610] This is calculated on a rolling basis with overlapping windows; for instance, the first quarter 2007 net charge-off rate is defined as the sum of the net charge-off rates from the first quarter of 2007 through the first quarter of 2009, while the second quarter 2007 net charge-off rate is defined as the sum of the net charge-off rates from the second quarter of 2007 through the second quarter of 2009.
[611] To arrive at the 93rd percentile, the Board reviewed the period between 1954 (the beginning of the post-war expansionary period) and 2009 (the conclusion of the 2008 financial crisis period). This window was chosen to capture multiple complete business cycles. In this 56-year period, there were nine recessions, four of which were severe. Thus, the frequency of severe recessions is 4/56, leading to the selection of the 93rd percentile. This procedure is used across the supervisory stress test process to choose percentiles from unconditional distributions.
[612] While no firm reports data on this schedule, certain firms have small balances of international auto loans reported on FR Y-14Q, Schedule M.1 (Balances). These balances are not large enough to meet the materiality threshold for reporting FR Y-14Q, Schedule A.1 (International Auto Loan).

Because a full business cycle of information is not available, aligning loss rates based on the frequency of severe recessions in historical data is not reasonable. Given these considerations, the Board instead calibrates the scalar loss rate based on the maximum observed 9-quarter (or 27-month) loss rate in the available historical data. This methodology yields a 9-quarter loss rate of 0.34 percent, which is equivalent to a loss rate of 0.0375 percent per quarter. The assigned loss rate balances the need to provide estimates of losses under stress with the constraints of the limited historical data and low materiality. Given the limited materiality of the portfolio and low assigned loss rate, the impact of applying this loss rate, as opposed to other plausible loss rates, is minimal.

For the Retail Non-Purpose loan portfolio,[613] there is no segment-level FR Y-14Q schedule. Because of this constraint, limited data on the risk characteristics or historical losses of these loans are available. Limited historical loss information is reported on FR Y-14A, Schedule A (Summary), but these data do not cover any periods prior to 2013. However, based on the characteristics of the portfolio, the Board expects losses on these loans to be low, even during a recession. First, the limited historical loss data that is available indicates that loss rates are minimal, and often 0 percent. Second, Retail Non-Purpose loans are generally secured by liquid assets such as securities with daily collateral monitoring by the firm, and most covered firms require margin calls to be met within 3 to 5 days. Loans tend to have strict loan-to-value ratio requirements to prevent collateral values falling below the value of the loan. With these strict risk management conditions in place, firms are well situated to recover the loan balance even in the case of default, by liquidating the collateral associated with the loan.

[613] As described earlier in this model description, the Board has proposed changes to the FR Y-9C and FR Y-14 instructions that may impact the balances reported as retail non-purpose loans in the supervisory stress test. *See* Section G.ii.a.(1) for more details.

Because of the limited historical data available for calibrating losses on Retail Non-Purpose loans, the Board also considered other loan categories with similar characteristics when calibrating the loss rate for Retail Non-Purpose loans. In particular, related categories include "purpose loans"—which are loans extended for the purpose of purchasing and carrying securities—as well as wholesale non-purpose loans—which are loans collateralized by securities not for the purpose of purchasing and carrying securities that are extended to a non-individual or for an investment or commercial purpose.[614] Similar to Retail Non-Purpose loans, purpose loans and wholesale non-purpose loans have low historical loss rates, and have characteristics similar to those described in the previous paragraph that make it likely that loss rates will remain low even during a period of economic stress.

Given the strict risk management conditions and low historical loss rates on Retail Non-Purpose loans and other loan categories on firm balance sheets with similar characteristics, the Board assigns a loss rate to these balances of 0.0625 percent per quarter (0.25 percent per year). This value is calibrated using historical loss rates and a review of firm internal projections of stressed losses on these loans, and is aligned with that of loans for purchasing and carrying securities. Because of the limited information available to precisely calibrate projected losses under stress, the assigned loss rate is on the conservative end of the range of reasonable estimates. This is appropriate and in line with the stress testing principle of conservatism, given the limited data available for this portfolio.

The values of the constant charge off rates for each of the six portfolios using a scalar model are listed in Table G8.

[614] For more information, *see* discussion of "margin loans" in Section A.d.2 (Corporate Model).

Table G8 - Loss Rates Applied to Scalar Portfolios

Portfolio	**Projected 9-Quarter Loss Rate**	**Projected Quarterly Loss rate**
Intl Home Equity Loan	1.84	0.2042
Intl First Mortgage	1.52	0.1690
Intl Other Consumer Loan	22.78	2.5313
Intl Small-Business Loan	5.05	0.5615
Intl Auto Loan	0.3375	0.0375
Retail Non-Purpose Loan	0.56	0.0625

(4) Projection of Loan Losses and Provisions

The models are used to project loan losses and provisions during the 13-quarter projection period.[615] The process for using the models to produce these values is described in this section.

Domestic Models

The estimated coefficients for each of the Domestic Models is applied to the data described in Section G.ii.a.(2) to project losses under the supervisory stress test. Firm data reported in the quarter immediately prior to the start of the projection period are used to determine balances and net charge-off rates by segment, while macroeconomic variables are taken from the Stress Test Scenarios. These data are used to project net charge-off rates for each segment within each portfolio for each firm in the first projection quarter. For the second and succeeding projection quarters, the process is the same, except that the projected net charge-off rate from the previous quarter, rather than the actual net charge-off rate (which may not have been observed yet), is used to project net charge-off rate in a given quarter.

[615] The supervisory stress test produces projections of firm balance sheets over 9 quarters. An assumption in the supervisory stress test is that firms will hold an allowance covering losses over the succeeding four quarters, necessitating 13 quarters of projections to allow for the calculation of allowance levels in all 9 quarters.

Note that in all cases, projected net charge-off rates are floored at zero. Negative net charge-off rates for certain segments are in the historical data are uncommon but are observed in some cases. Negative net charge-off rates can result from recovery on loans in a segment in a quarter being greater than gross losses for that segment in that quarter. When negative net charge-off rates arise in the historical data used for estimating the model parameters, the Board uses these negative net charge-off rates as reported, with no floor or adjustment. However, when using the model to project loss rates, the Board applies a zero floor to projected net charge-off rates. This is because the Board determined that while negative net charge-off rates are possible, they are uncommon, and especially unusual during periods of economic stress. Applying a zero floor is consistent with the stress testing principle of focusing on the ability to evaluate the impact of severe economic stress from the Stress Testing Policy Statement.

The process outlined above yields a time series of projected net charge-off rates for each segment within each portfolio for each firm. The projected net charge-off rates are then aggregated across segments within each portfolio based on the balance reported in each segment immediately prior to the start of the projection period to produce a time series of projected net charge-off rates for each portfolio for each firm.

The models assume that the balance in each segment within each portfolio for each firm remains constant throughout the projection period.[616] This assumption is consistent across the loan loss models used in the supervisory stress test, which generally assume a constant balance sheet over the stress test horizon. This assumption is consistent with the principle that the supervisory stress test is meant to demonstrate whether access to credit would remain available

[616] Because the Board does not model loan-level loss rates, new loans originated during the forecast period are implicitly assumed to have the same risk profile as loans that charged-off during the period.

under a hypothetical recession because it assumes that firms would maintain their lending portfolio at the same level throughout the projection horizon.

The process for projecting net charge-offs outlined in this section is repeated for each of the four Domestic Models. For Student loans, the net charge-off rate is only assigned to private student loan balances designated as "in repayment." As described in Section G.ii.a.(3), government guaranteed student loan balances are not incorporated into the regression; instead, these balances are assigned a fixed loss rate of 0.135 percent per quarter.[617] Since balances not in repayment (i.e. those that are in deferment, in forbearance, or in a grace period) require no payments, they are assumed to have zero losses over the stress test horizon.

International Model

The process for projecting net charge-off rates for the International Cards Model is similar to that used for the Domestic Models, except that both delinquency rate (from Equation G2) and net charge-off rate (from Equation G3) are projected. Similar to the Domestic Models, projected values of delinquency rate and net charge-off rate are used to project these values in the succeeding quarters. Projected net charge-off rates are aggregated across geography segments, but net charge-off rates for International Bank and Charge Cards are left separate from those of International Small Business and Corporate Cards for each firm.

Additionally, two variables used in the International Cards Model, the Mexico real GDP growth rate and the Euro Area unemployment rate, are not included in the Stress Test Scenarios. Instead, the Board projects these values using a linear regression model estimated on historical macroeconomic data. To produce projections of the Euro Area unemployment rate during the supervisory severely adverse scenario, the Board estimates a regression model that uses

[617] *See* Section G.ii.a.(3) for support for setting this loss rate.

historical data from 1970Q2 to 2025Q1 to project the Euro Area unemployment rate based on the Euro Area GDP growth rate, its two lags, and on two lags of the unemployment rate itself. The Board then applies the fitted coefficients from this regression model, as well as the projected values of these variables in the Stress Test Scenarios, to produce projections of the unemployment rate in the Euro Area. To produce projections of the Mexico real GDP growth rate during the supervisory severely adverse scenario, the Board estimates a linear regression model that uses historical data from 2007Q1 to 2014Q1 to project the Mexico real GDP growth rate based on certain variables included in the Stress Test Scenarios—namely, U.S. GDP growth, lagged U.S. GDP growth, Euro Area GDP growth and Developing Asia GDP growth. This time period is chosen to estimate the spillovers from the global economy to the Mexican economy following a global financial shock, as captured by the 2008 financial crisis and the subsequent recovery. The Board then applies the fitted coefficients from this regression model, as well as the projected values of these variables in the Stress Test Scenarios, to produce projections of the Mexico real GDP growth rate.

Scalar Models

For the portfolios that use scalar models, the quarterly net charge-off rate in Table G8 associated with a portfolio is applied for each quarter in the projection period to all balances for that portfolio.

(5) Loss Aggregation

The above descriptions of the process for projecting losses on the Domestic Models, International Model, and Scalar Models describe the process for producing quarterly net charge-off rates for each firm within each portfolio. This section describes how these projected net charge-off rates are used to project losses in dollar terms.

For firms reporting data on the relevant schedule defined in Table G3 for each portfolio using a regression model, the quarterly net charge-off rate is applied to the quarterly balance output by the balance sheet line-item projections calculator.[618] In line with the constant balance sheet assumption, portfolio balances are projected to remain constant in each projection quarter. For all firms with positive balances in each portfolio using a scalar model, the constant loss rate is applied, regardless of whether the firm reports data on the relevant schedule defined in Table G3.

Firms with positive balances reported on the FR Y-14Q, Schedule M (Balances) that do not meet the materiality threshold for reporting on the schedules defined in Table G3 have the option of reporting or not reporting those schedules. For the regression models, all firms reporting the relevant schedule are assigned a modeled loss rate, regardless of whether the firm is required to submit the schedule. Firms who choose not to report a schedule for which balances are non-zero but less than the materiality threshold are assigned the equivalent loss rate path to the 50th percentile firm in terms of loss rate. Firms that are required to report data on the relevant retail schedule but do not do so, or whose data quality is insufficient for use in modeling, are conservatively assumed to have the equivalent loss rate path to the 90th percentile firm in terms of loss rate. In each case, the percentiles are based on 13-quarter loss rates; if no firm sits at exactly the 50th or 90th percentile, respectively, the firm with the loss rate immediately above this level is used.

Total losses are used in the downstream Provisions Model[619] to produce estimates of provisions. A final consideration is that the Other Retail Models project net charge-offs, a form of accounting losses, unlike other loan loss models in the supervisory stress test, which project

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[618] *See* Section A of the Aggregation Models Description (Balances Model).
[619] *See* Section B of the Aggregation Models Description (Provisions Model).

expected losses, a form of economic losses. The Provisions Model makes an adjustment for several of the Other Retail portfolios (specifically, the portfolios using regression models) to account for the differences between the timing of the realization of accounting losses compared to economic losses.

b. Support for Model Decisions

This section provides additional support for model decisions, in addition to the support provided in the description of the model.

(1) Regression models

Top-Down Modeling Approach

As previously described, the Board uses regression models for portfolios that are sufficiently large, and for which there is sufficient historical loss data, to project net charge-off rates based on reported data and projected macroeconomic characteristics with sufficient precision. The regression framework outlined above balances the stress testing principle of simplicity and the stress testing principle of accuracy. Within each of the Other Retail portfolios, there is significant variation across firms in terms of types of lending, only some of which can be captured by reported variables. For instance, the Other Consumer portfolio includes recreational vehicle loans and boat loans as well as unsecured personal loans and certain home renovation loans. Given the wide variety of loans captured in each of the portfolios, and the different business strategies of each firm, it would be challenging to individually model each type of loan. The regression models use a simple, consistent approach that produces reasonable results despite the variety of loans included in each model, while remaining sensitive to variation in both the input portfolio data and the projected macroeconomic scenario.

In particular, the regression models rely on the previous value of net charge-off rate (and for the International Model, the delinquency rate) to project future net charge-off rates. This structure of relying on previous values is referred to as an "autoregressive structure," and is justified for two reasons. First, it accounts for persistence in firm portfolio performance; riskier portfolios empirically tend to stay riskier over the short and medium term, as evidenced by the positive and statistically significant coefficients on the previous value of the net charge-off rate. One limitation to the structure is that it does not account for when firms have large discrete changes to their portfolios. For instance, if a firm sells off a risky portion of the portfolio, the model may over-predict the net charge-off rate in the next quarter, because the model does not fully account for the reduced risk in the portfolio. However, this risk is partially addressed by the segmentation in the model, which accounts for changes over time to the portfolio composition. Second, it allows for the model projections to be produced using limited data. Given the bespoke nature of many of the loans in these portfolios, capturing all of the relevant characteristics to produce a "bottom-up," loan-level approach would be challenging, and require a notable increasing in reporting burden for firms. By relying on previous values of net charge-off rate, the model can account for differences in riskiness across firms that cannot be easily captured by other variables without increasing the amount of reported data.

Additionally, the model is estimated using weighted least-squares, where observations are weighted by the risk segment's outstanding balance in a given quarter. This prevents smaller segments, which have much more volatile reported net charge-off rates that are susceptible to outliers, from unduly influencing the model estimates.

Compared to a more complex modeling structure or a structure that varies more substantially across the different models, the Other Retail regression models produce results that are easily communicable, understandable, and analyzable. The segment-level approach is also able to produce accurate models, as demonstrated in academic literature,[620] and has been applied in other in regulatory modeling contexts.[621] The approach also minimizes manual and automated resource requirements, and by limiting the required data reporting to the most important features, reduces the likelihood of a reporting error leading to unreasonable results. Finally, the Board conducts regular performance testing to assess model performance—including the use of benchmark models, where applicable, performance testing and monitoring, and sensitivity analysis, which isolates the effect of a change in one model input on the eventual model output. This performance testing has demonstrated that the models are producing reasonable and reliable results. Model performance is monitored regularly to ensure that it remains appropriate for use. Based on these factors, the Board believes that the chosen modeling approach is appropriate for the Other Retail portfolios using regression models.

Two Equation Structure for International Cards Model

While the Domestic Models project net charge-off rates using a single equation, the International Cards Model employs a two-equation model that separately projects delinquency rates and net charge-off rates simultaneously. The projected delinquency rates and net charge-off rates in a given quarter are then used to project the succeeding quarter's net charge-off rates.

The benefit of including delinquency rates, in addition to net charge-off rates, is that the two-equation structure incorporates additional information about differences in risk levels across firms into the model that cannot fully be captured by net charge-off rates. For portfolios where

[620] *See*, for instance, Hale, Krainer, and McCarthy (2020). Galina Hale, John Krainer, and Erin McCarthy, 2020. "Aggregation Level in Stress-Testing Models," International Journal of Central Banking.
[621] *See*, *e.g.*, Correia et al. (2022). Sergio Correia, Matthew P. Seay, and Cindy M. Vojtech, 2022. "Updated Primer on the Forward-Looking Analysis of Risk Events (FLARE) Model: A Top-Down Stress Test Model", Finance and Economics Discussion Series.

differences across firms are meaningful and cannot be easily captured by other variables, incorporating a second equation is valuable.

The trade-off is that including multiple equations can cause the model to become overly sensitive to the previous values of variables, crowding out other features, such as the macroeconomic environment. While this might lead to the model appearing more accurate based on in-sample fit, it can become problematic to rely on these variables over the course of the entire projection period, as small errors in the projection can compound over the course of 13 quarters.

For the Domestic Models, the Board determined that the single equation structure produced reliable model results, and that adding additional equations would not lead to more reliable projections because of the reduced sensitivity to macroeconomic variables. However, for the International Model, model sensitivity to variations in portfolio risk improved when the second equation was included, sufficient to justify the two-equation approach.

Based on this analysis, the Board uses the two-equation approach for the International Cards Model, while relying on a single equation for Domestic Models.

Given the Board's decision to use a two-equation approach for the International Cards Model, the Board next considered what threshold should be used to define loans as delinquent. The instructions for FR Y-14Q, Schedule A.3 (International Cards), Field A.4 ("Delinquency status") segment loans into five delinquency statuses, based on delinquency status as of month-end:

- Current and 1-29 days past due
- 30-59 days past due
- 60-89 days past due
- 90-119 days past due
- 120 or more days past due

Ultimately, the Board determined that defining delinquency rate based on the share of balance that is either 60-89 days past due, 90-119 days past due, or 120 or more days past due was appropriate for use in the International Cards Model. A definition of delinquency that is too expansive—such as one that includes loans that are 30-59 days past due—risks inappropriately mixing borrowers who have short-term liquidity issues or consumer errors (such as an autopay failure) from borrowers with more sustained payment difficulty. However, a definition of delinquency that is too constrained—such as one that includes only loans that are 90 or even 120 days past due—risks missing informative data on delinquency that is meaningful for predicting future net charge-off rates. Furthermore, the more expansive definition is robust to differences in firm charge-off behavior, as historical FR Y-14Q data indicates that certain firms are more likely than others to charge-off loans before they reach 120 or more days past due. The Board determined that defining delinquency based on a threshold of 60 or more days past due was appropriate to consider an expansive range of defaults without incorporating additional noise that may be reflective of factors other than sustained payment difficulties.

Quarterly Modeling Frequency

The regression models each produce loss projections for each quarter in the projection period. This is despite the fact that firm data are available monthly via the FR Y-14Q (firms report data once a quarter, but data are reported separately as of each reporting month within the quarter) or FR Y-14M (firms report data each month). However, the stress test scenarios use quarterly macroeconomic projections, and the models are used to project loan losses and provisions in each quarter of the stress test projection period. Therefore, the additional granularity from producing monthly projections does not have substantial benefit for producing stress test results. Additionally, aggregating monthly data to quarterly data smooths volatility that can exist in the monthly data, leading to more stable projections.

Macroeconomic and Other Variables

Domestic Models

Consistent with other forms of retail lending, the Other Retail portfolios tend to be sensitive to changes in household economic conditions. When economic conditions worsen, borrowers struggle to pay their bills, leading to increased default rates. The Domestic Models proxy for economic conditions using the quarterly change in the U.S. unemployment rate.

The use of unemployment rates to proxy for broad economic stress is supported by academic literature on credit risk, industry best practices, and the Board's experience and expertise. Unemployment rates are broadly used in this context because they provide a comprehensive measure of the economic health of households and businesses. Higher unemployment rates can be an indication of businesses cutting costs in the face of falling demand and stress on household budget constraints. These situations can lead businesses (including small businesses, loans to which are modeled using the Other Retail Models) and households to default on their loans. The importance of unemployment rate is observed in academic literature across different retail loan products, including first lien mortgages (see, for example, Elul, Souleles, et al., 2010); home equity lines of credit (Hale, Krainer, and McCarthy, 2020) and credit cards (see, for example, Agarwal and Liu, 2003; and Bellotti and Crook, 2009)[622].

Because the unemployment rate proxies for job and income loss, an increase in the unemployment rate is associated with higher net charge-off rates. In line with the stress testing

[622] Bellotti, T., & Crook, J. (2009). Credit scoring with macroeconomic variables using survival analysis. Journal of the Operational Research Society, 60(12), 1699-1707.

principle of simplicity and to reduce reporting burden, the FR Y-14Q does not capture geographic information for the portfolios within the Domestic Models; therefore, the national-level unemployment rate is used. As a result, the Domestic Models do not account for regional variation in economic conditions. Despite this, the national unemployment rate is strongly associated with net charge-off rate in the historical data.

While the quarterly change in the U.S. unemployment rate enters each of the Domestic Models in some form, the exact specification varies. As detailed in Table G6, in certain models, the contemporaneous change is used; in other models, the previous quarter's change is used; and in others, both are included. The Board relied on a combination of economic intuition and statistical fit using coefficient significance to determine the appropriate specification of the change in unemployment rate that enter the Domestic Models.

For the Private Student Loan equation, the level of the unemployment rate is included in addition to the quarterly change. As described in Section G.ii.a.(3), the Board determined the inclusion of the level of the unemployment rate in this model was justified based on its alignment with student loan loss rates during the 2008 financial crisis period.

Finally, the private student loan portfolio also includes the calendar quarter in the model to capture the effects of seasonality. While the other Domestic portfolios do not appear to have strongly seasonal net charge-off behavior, the net charge-off rate on private student loans is meaningfully higher in the fourth quarter compared to other parts of the year, based on the finding that the coefficient on the variable for observations in the fourth quarter is statistically significant.

International Model

The International Cards Model is used to project losses on loans that are located around the world. Because economic conditions can vary significantly across regions, the Board considered how to account for the macroeconomic environment in the model. The model includes variables that capture global economic conditions as well as variables that capture regional economic conditions. To account for global economic conditions, the Board uses the quarterly change in unemployment rate due to its strong correlation with economic conditions in other countries during the 2008 financial crisis period. The use of a single variable to capture global conditions is consistent with the relevant literature in the field.[623] Furthermore, the severely adverse scenario considers a severe global recession, in which stresses on U.S. businesses and households, proxied by the U.S. unemployment rate (as discussed previously with regard to the Domestic Models), can spill over to foreign economies given global interconnectedness. In this context, it is prudent to account for global conditions when projecting net charge-off rates for international loans. While global economic conditions are relevant, the Board believes based on historical experience that region-specific economic conditions can also be relevant to projecting net charge-off rates; as default risk is higher in locations experiencing more economic stress. Therefore, to account for local economic conditions, the Board uses the variables described in Section G.ii.a.(3)**Table** .

More specifically, the delinquency rate equation (Equation G2) includes both local and global macroeconomic variables to capture the region-specific and global market conditions.

[623] *See*, *e.g.*, Rey (2018). Hélène Rey, 2018. "Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence," NBER Working Papers 21162, National Bureau of Economic Research, Inc.; Using measures of both global and regional conditions is also seen elsewhere, as in Xia and Zhou (2023). Xia, Tian and Zhou, Hang, 2023. "Commodity terms of trade co-movement: Global and regional factors," Journal of International Money and Finance.

Since the net charge-off rate equation in Equation G3 already incorporates these through the delinquency rate in Equation G3, fewer macroeconomic variables are directly included in this equation.[624]

To account for global economic conditions in the delinquency rate equation, the quarterly change in the U.S. unemployment rate in the previous quarter is used. This variable is applied to balances in all four regions in the International Cards model. To assess reasonability of using the U.S. unemployment rate as a measure of global economic conditions, the Board reviewed historical correlation between the U.S. unemployment rate and other region-specific macroeconomic factors. This review demonstrated that the U.S. unemployment rate is highly correlated with other regional factors, especially those of proximate locations such as Canada and Mexico. The use of the U.S. unemployment rate to proxy global economic conditions therefore does create the possibility that the model will not reliably predict losses isolated to particular regions; however, the assumption that the U.S. unemployment rate can serve as a proxy for global economic conditions remains broadly appropriate due to the increasingly interconnected nature of the global economy and the U.S. unemployment rate's high correlation with other regional factors.

Meanwhile, proxies for local economic conditions in the International Cards model are chosen to align with the concentration of loans within a region. For the Canada region, in light of the historical correlation between U.S. and Canadian economic conditions, the U.S. real GDP growth rate is used in the delinquency rate equation. For the EMEA region, the change in the Euro area unemployment rate is used to proxy for local economic conditions, which is used in both the delinquency rate equation and the net charge-off rate equation. This is supported by the

[624] Recall from earlier in this section, in "Two Equation Structure for International Cards Model," that a trade-off of the two-equation approach is reduced sensitivity to other variables, including macroeconomic variables.

fact that the majority of balances in this region are concentrated in Europe. Because the Euro Area unemployment rate predicts net charge-off rate effectively for balances in the EMEA region, and the correlation between U.S. unemployment rate and the Euro Area unemployment rate is weaker than that of the U.S. unemployment rate and proxies for other regions' economic conditions, EMEA balances use only the Euro Area unemployment rate, and not the U.S. unemployment rate, in the net charge-off rate equation. For the LATAM region, which consists almost entirely of loans in Mexico, Mexico GDP growth rate is used to proxy for regional economic conditions. Finally, for the APAC region, the developing Asia real GDP growth rate, as defined in Section G.ii.a.(3), is used to proxy for regional economic conditions, to reflect the broad performance of economies throughout the region.

In addition to the above, the Board considered increasing the number of regions reported on FR Y-14Q, Schedule A.3 (International Cards), to increase the granularity over which projections can be made. However, due to the relatively small balances in the portfolios, defining more regions could lead to sparse segments, and unreasonable loss projections. Additionally, increasing the number of geographic regions would increase the reporting burden of the schedule, without meaningful improvement in projections. For these reasons, the Board believes that the four regions defined on the schedule are sufficient to account for localized conditions without creating sparse segments or creating unnecessary reporting burden.

(2) Scalar models

This sub-section discusses the use of a scalar approach for these models, as opposed to more complex approaches. Further details are available in Section G.ii.d.(2). For support for the calibration of the scalar models, see Section G.ii.a.(3).

As described in Section G.ii.a, scalar models are used for these portfolios due to some combination (varying by portfolio) of sparseness of reported data and limited balances in the portfolio reducing the impact of loss projections in these portfolios on stress testing results.

Throughout the historical data reported on FR Y-14Q, Schedule A (Retail), a smaller number of firms report data on the international schedules compared to the domestic schedules; even among firms that do report, the total balances are generally small. In recent years, balances have fallen further in these portfolios, as firms have reduced exposure to international loans.

The limited historical and recent data support the use of scalar models for multiple reasons. Because of limited historical data, there are fewer historical observations to use to fit a regression model, reducing the precision of the model estimates. In certain cases, despite concerns about sparse historical data, regression models are used. For example, in the International Cards Model, due to sparse historical data, the data from the International Bank and Charge Card and International Small Business and Corporate Card portfolios are pooled to create a single regression; this is justified due to the relatively high impact of loss projections in these portfolios on stress test results. However, with the other international portfolios, there are no obvious portfolios to pool to produce a reasonable model; furthermore, balances in these portfolios are less material, reducing the benefits of implementing a more complex model and reducing the likelihood that imprecision in the scalar approach will impact capital requirements for any firm.

As is further discussed in Section G.ii.d.(2), in the Retail Non-Purpose Loan portfolio, the historical data availability constraints are more significant. While balances in this portfolio are high, increasing the benefits of a more complex modeling approach, the Board is limited by the historical loss data available for this portfolio. Therefore, a scalar model is used for this portfolio as well.

c. Adjustments and Data Cleaning Steps

The Board's general practice is to use all historical data reported on the FR Y-14M and FR Y-14Q, Schedule A to estimate the Regression and Scalar models. To ensure outliers and missing data do not negatively impact the model, certain treatments are applied:

- Certain observations are erroneous (based on communications from the reporting institutions) or extreme outliers. The process for identifying erroneous or extreme outliers involves plotting firm-level time series for key summary metrics used in Other Retail Models and then comparing these observations to historical performance to identify any significant deviations. In general, when the Board identifies problematic data, it generally requests that the reporting institution resubmit the affected period. However, in cases where a resubmission is not possible, or when the firm confirms that the reported observations are correct despite being extreme outliers, the Board will then exclude these observations from the input data used to estimate the model.
- In certain cases, erroneous data are not corrected in the FR Y-14Q report, but the reporting institution provided supporting documents that allowed the Board to correct the input data. In these cases, the affected observations are corrected and then used in the data.
- In certain cases, firms which had historically reported FR Y-14Q schedules, but at the time the model parameters were estimated were no longer reporters of the FR Y-14, were removed entirely from the estimation data. The Board determined that this is appropriate, as using historical data from firms that are no longer subject to the FR Y-14 reduces the representativeness of the estimation data.

In addition to the above treatments, the Board cleans the data for use in the model, as follows:

- For the Domestic Small Business and Corporate Credit Card portfolio, data were reported on a since-retired FR Y-14Q schedule covering the period from the first quarter of 2007 through the first quarter of 2012. Reporting then changed to be on the FR Y-14M from June 2012 through the present reporting period (reported using credit card type "3 – Business Card" and "4 – Corporate Card"). This change in reporting requires several adjustments to the stress test models. First, to fill the two-month gap when the portfolio was not reported on either form, the Board assumes that April 2012 reported data is equivalent to March 2012 reported data, and that May 2012 data is equivalent to June 2012 reported data. Additionally, the data reported on FR Y-14M, Schedule D.1 (Credit

Cards – Loan Level) is aggregated to the segment-level to align with the FR Y-14Q formatting, using the following mapping in Table G9:

Table G9 - FR Y-14M Variables Used in Small Business and Corporate Credit Card Model

Segment Level Variable	Definition (All line items from FR Y-14M, Schedule D.1)
$ Outstanding	Line Item 15 ("Cycle Ending Balance") if available; Line Item 122 ("Month Ending Balance") otherwise. Summed across all loans in a segment and divided by 1,000,000.
$ Gross contractual charge-offs	Line Item 62 ("Gross Charge-off Amount – Current Month") if Line Item 69 ("Bankruptcy Flag") is set to 0. Set to zero if Line Item 69 ("Bankruptcy Flag") is set to 1. Summed across all loans in a segment and divided by 1,000,000.
$ Bankruptcy charge-offs	Line Item 62 ("Gross Charge-off Amount – Current Month") if Line Item 69 ("Bankruptcy Flag") is set to 1. Set to zero if Line Item 69 ("Bankruptcy Flag") is set to 0. Summed across all loans in a segment and divided by 1,000,000.
$ Recoveries	Line Item 63 ("Recovery Amount – Current Month). Summed across all loans in a segment and divided by 1,000,000.
$ Net charge-offs	Sum of "$ Gross contractual charge-offs" and "$ Bankruptcy charge-offs" minus "$ Recoveries"
Product Type (Small Business Card or Corporate Card)	Line Item 3 ("Credit Card Type"). Small business cards are defined as when this field is set to "3." Corporate cards are defined as when this field is set to "4."

- From the third quarter of 2020 through the first quarter of 2021, the FR Y-14Q instructions required covered firms to report "Dollars Under Federally Guaranteed Programs" (such as Paycheck Protection Program loans) on the FR Y-14Q, Schedule A.9 (U.S. Small Business). Because these loans are guaranteed by the government and were only reported on this schedule for these three quarters, including these balances would lead to results that are not representative of the portfolio currently reported on the schedule. Therefore, balances associated with Paycheck Protection Program Loans are removed from the total segment balance for the quarters in which they were reported.
- In certain portfolios, segmentation was added to the FR Y-14Q reporting after covered firms had begun reporting, meaning that certain segments disaggregated in some prior periods. In one case, this is relevant for definitions used in the Other Retail Models. In particular, on FR Y-14Q, Schedule A.9 (U.S. Small Business), a loan's secured/unsecured status (field A(5)) was not reported prior to 2012. Firms that joined the panel following the addition of this field to the schedule report them in historical data, but they are unavailable for firms that were reporting prior to the addition of the new field. For data from the latter group of firms, the Board must make assumptions regarding how to fit the non-disaggregated data into the model segments. In particular, the Board assumes that all

loans that were reported prior to the adoption of the secured/unsecured variable are treated as unsecured loans. This treatment reflects the Board's analysis of key loan characteristics, which revealed that metrics such as average loan size and net charge-off rate of the missing collateral portfolio were more similar to that of unsecured loans than to that of secured loans.

Macroeconomic data are incorporated into the model using the same format for both estimating the model and producing loss projections. To project losses using these models, the models input values from the supervisory stress test scenarios.

Additionally, as described in Section G.ii.a.(5), the process used to project losses varies for each firm based on its reporting behavior. These steps are detailed below:

- For firms that are not required to report a given schedule listed in Table G3 (due to not meeting the materiality threshold for that schedule) but choose to do so anyway, the reported data is generally used to produce a modeled loss rate for the relevant portfolio.
- For firms that are not required to report a given schedule listed in Table G3 (due to not meeting the materiality threshold for that schedule) and do not report, balances in that portfolio for that firm are assigned the loss rate path of the 50^{th} percentile (median) firm among reporting covered firms, based on the 13-quarter projected loss rate. In cases where no firm is exactly at the 50^{th} percentile, the firm above the 50^{th} percentile that is closest to the 50^{th} percentile is used.
- For firms that are required to report a given schedule, but do not do so, or for which data quality is materially deficient, the Board makes efforts to request submissions or resubmissions. If data quality remains deficient, balances in that portfolio are assigned the loss rate path of the 90^{th} percentile firm among reporting covered firms, based on the 13-quarter projected loss rate. In cases where no firm is exactly at the 90^{th} percentile, the firm above the 90^{th} percentile that is closest to the 90^{th} percentile is used.
- In cases where data are reported deficiently or where other challenges are identified with using reported data (for instance, when a firm divests a portfolio mid-quarter), the Board reserves the right to exclude these data from being used in projections. This avoids the situation where problematic data would be used to set the 50^{th} or 90^{th} percentile calculation for other covered firms in the above scenarios.

Finally, the Board compares the aggregate balances reported on the schedules for each portfolio listed in Table G3 to balances reported on FR Y-14Q, Schedule M (Balances) to which the projected loss rates are applied. In certain cases, the definitions of the two schedules may not exactly align, causing discrepancies between the population of loans used to project the net charge-off rates and the loans to which these net charge-off rates are applied. When such discrepancies are identified, the Board may propose changes to the FR Y-14 instructions to bring the schedules into alignment; however, this is subject to delays based on the schedule on which the reporting forms are updated. The Board monitors the discrepancies to ensure that impacts do not become material; generally, reported data are not adjusted based on these discrepancies.

d. Alternatives

(1) Regression Models

Alternative Model Structures

The Other Retail regression models use an autoregressive structure to project net charge-off rates based on previously observed values of net charge-off rates, risk-segment specific terms, and macroeconomic variables. The Board considered several alternatives and concluded that the autoregressive structure was the simplest approach that produced accurate, reliable and robust results.

Bottom-up Approach

One alternative approach is to model the portfolios from the bottom-up, calculating the probability of default (PD), exposure at default (EAD), and loss given default (LGD) for each loan in the portfolio and use that to calculate the total expected losses. This methodology is used to model other loan losses in the supervisory stress test. One advantage of this approach is that default rates based on past due status are a more timely reflection of economic losses; by comparison, net charge-offs may lag defaults. However, this approach is not used in the Other Retail models due to limitations of the input data, as generally historical data and current portfolio data are available only at the segment level rather than the loan level.[625] Given the lack

[625] Among Other Retail portfolios, only the small-business and corporate credit card portfolio has loan-level data reported on the FR Y-14M, which allows for a potential bottom-up approach. However, the portfolio combines the

of loan-level data that would be necessary to build a bottom-up model for the Other Retail portfolios, the Board concluded that the top-down approach—which is a well-established and practical alternative in regulatory modeling to assess the systemic risk using aggregated data—was appropriate.[626]

Scalar Model

Another alternative approach, contrasting in terms of complexity from a bottom-up model, is to use a scalar model for all 12 portfolios within the Other Retail model. This approach applies a single loss rate path to all firms reporting balance for a given portfolio. This approach is currently applied to a subset of the portfolios within the Other Retail models (see Table G2). This approach has the advantage of being operationally simple and provides a consistent treatment across covered firms; however, it does not account for true differences in riskiness across covered firms, or variation based on the severity of the scenario. By contrast, the regression models chosen for the Domestic and International portfolios incorporate segmentation and the previous value of the net charge-off rate, allowing the differentiation in riskiness across firms in a portfolio to be recognized. As a result, the Board determined that the scalar model alternative would produce less precise projections than the regression model approach.

Multi-Equation Model

A third alternative approach would be to use a multi-equation model for all the regression models, similar to the International Cards Model. Compared to the single-equation net charge-off rate model, a multi-equation model takes into account additional features, such as delinquency rate, which can improve model fit. However, as described in Section G.ii.b.(1),

segment-level data from the FR Y-14Q before June 2012 and aggregated loan-level data from the FR Y-14M afterward, making bottom-up modeling difficult due to data inconsistency.

[626] *See*, *e.g.*, Correia et al. (2022).

there are trade-offs in using multiple equations, especially when using the model to project losses over many periods—when small errors in projected values can compound. The Board determined these trade-offs were justified for the International Cards portfolio, but not for the Domestic Models, which have strong model fit using a single-equation structure.

Additionally, as discussed in Section G.ii.b.(1), the Board considered alternative definitions of the delinquency rate used in Equation G2, such as using the share of loan balance that is 30 or more days past due or 90 or more days past due, rather than the 60 or more days past due definition used in the International Cards Model. The Board decided to use a threshold of 60 or more days past due to balance considering an expansive range of defaults without incorporating additional noise that may be reflective of factors other than sustained payment difficulties.

Alternative Segmentation

The Other Retail regression models rely on simple segmentation to maximize explanatory power while maintaining a simple approach. The chosen segmentation is shown in Table G5. The Board considered more complex segmentation. However, the Board determined simple segmentation was appropriate because, while dividing the portfolios into additional risk segments has the advantage of better capturing the riskiness of different types of loans, it increases the potential for creating very small segments with limited sample sizes, raising the risk of spurious relationships. Note that for all portfolios, delinquency status and loan age were not considered as segmentation variables, as they are dynamic and would be expected to shift through the projection horizon. Only static variables were considered when segmenting the portfolios.

Domestic Other Consumer

In the Domestic Other Consumer portfolio, the “Product type” (FR Y-14Q, Schedule A.7, U.S. Other Consumer, Field A.1) is used for segmentation. The reported variable is divided into five categories: “secured-revolving”; “secured-installment”; “unsecured-revolving”; “unsecured-installment”; and “overdraft.” Among these categories, secured loans have consistently lower net charge-off rates than unsecured loans in the available historical data.[627] The Board considered other variables—including origination loan-to-value (LTV) and origination credit score—but ultimately the Board concluded that these other variables did not improve the model fit sufficiently to justify their inclusion. For example, while credit score is a key risk driver in the Other Consumer portfolio, the FR Y-14Q, Schedule A.7 only categorizes loans based on FICO® or equivalent of “>620,” “<=620,” and “missing.” Because the vast majority of balances fall into the “>620” category, there is insufficient variation for use in the model. Given the lack of improvement in model fit from including other variables, the Board determined it was appropriate to apply simple segmentation based on product type in the Domestic Other Consumer Portfolio.

Domestic Small Business

In the Domestic Small Business portfolio, the “Secured or unsecured” variable (FR Y-14Q, Schedule A.9, U.S. Small Business, Field A.5) is used for segmentation. Similarly to the Domestic Other Consumer portfolio, the presence of collateral is the most important factor in determining the loss rate of this portfolio. However, a loan’s secured/unsecured status (Field A.5) was not reported prior to 2012. Covered firms that began reporting FR Y-14Q, Schedule A.9 (U.S. Small Business) following the addition of this field to the schedule report it in

[627] Overdrafts, which make up a very small portion of reported balances in this portfolio, are treated as unsecured loans.

historical data, but this variable is unavailable for firms that were reporting prior to the addition of the new field. For data from the latter group of covered firms, the Board must make assumptions regarding how to fit the non-disaggregated data into the model segments. While this data limitation causes this variable to have incomplete coverage during the 2008 financial crisis period, the inclusion of this variable in the model still substantially improves the statistical fit of the model. For example, the model fit, as assessed by adjusted R-squared,[628] is notably better than an alternative model for the Domestic Small Business portfolio where segmentation is based on a combination of "Product type"[629] reported on FR Y-14Q, Schedule A.9 (U.S. Small Business), Field A.1 and "Original commercially available credit bureau score or equivalent" [630] reported on the FR Y-14Q, Schedule A.9 (U.S. Small Business), Field A.3.[631] While using these segments allowed for more granular risk differentiation and full coverage of the 2008 financial crisis, the lack of consideration of whether the balance is secured or unsecured fundamentally weakened the model fit. Because of the importance of secured status in predicting historical net charge-off rates, and the strong model fit segmenting based on this variable, the Board determined that using secured status to segment Domestic Small Business loans appropriately aligned with the objectives of the stress test.

Domestic Small Business and Corporate Credit Card

In the Domestic Small Business and Corporate Credit Card portfolio, segmentation options are limited based on what is available in the FR Y-14Q data used to estimate the model from 2007 through the first quarter of 2012. Thus, while credit score is available at a granular

[628] Adjusted R-squared is a measure of the share of the variation in the outcome variable that can be explained by the equation, adjusted based on the number of terms in the model. Values closer to 1 are reflective of better model fit.
[629] This field segments loans into categories for "Line of Credit," "Term Loan," and "Other."
[630] This field segments loans into categories for "<=620 (FICO® or equivalent)," ">620 (FICO® or equivalent)," and "N/A – Original credit score is missing or unknown."
[631] This historic model also used a three-equation structure, with equations corresponding to delinquency rate, default rate, and net charge-off rate.

level in the FR Y-14M data from June 2012 to the present, it is not feasible to use more granular risk segments, as they are not available during the 2008 financial crisis—a key period for the model as it captures the most critical relationship between macroeconomic conditions and credit risk. The most important characteristic available for modeling is product type (FR Y-14M, Schedule D.1, Line Item 7, “Credit Card Type”); corporate credit cards have consistently lower loss rates than small business credit cards, partly due to more stable borrower profile—employees with regular salaries—with added risk mitigation from internal control over spending and employer oversight. No other variable with a full history of data provided the level of explanation needed for the model.

Student Loan

In the Student Loan portfolio, in addition to segmenting by product type (in that government guaranteed loans receive a separate, fixed loss rate), credit score (“Original commercially available credit bureau score or equivalent”) reported on FR Y-14Q, Schedule A.10 (Student Loan), Field A.3 is used as the segmentation variable. Three categories are available in the data, corresponding to FICO® or equivalent less than or equal to 660 (“<= 660”), above 660 (“> 660”), and missing or unknown (“N/A— Original credit score is missing or unknown”). In practice, the vast majority of the balance falls into the “> 660” category. While the level of education pursued by the loan recipient (FR Y-14Q, Schedule A.10 (Student Loan), Field A.5, “Education level”) can be an important factor in understanding student loan performance, this field is unavailable during the 2008 financial crisis, and therefore, loan performance by this segment cannot be measured for that period. In contrast, credit score is available and provides a consistent way to segment loans based on risk.

International Cards

Finally, in the International Cards model, data are segmented by both product type and geography. Product type, reported under FR Y-14Q, Schedule A.3 (International Credit Card), Field A.1, divides loans into “Bank card,” “Charge card,” and “Corporate, SME,[632] and Business cards.” The Board aggregates these product types into two broader categories based on borrower type, specifically by combining “Bank card” and “Charge card” into a single segment, while leaving corporate, SME and business cards separate. This segmentation differentiates individual-purpose cards from business-purpose cards and helps capture key differences in risks while keeping the model structure less complex.[633] The geographic region, reported under FR Y-14Q, Schedule A.3 (International Credit Card), Field A.3, divides the International Card model into four regions – “Region 1: Canada,” “Region 2: EMEA — Europe, Middle East, and Africa,” “Region 3: LATAM — Latin America and Caribbean” and “Region 4: APAC — Asia Pacific.” The regions are further interacted with region-specific macroeconomic variables, allowing the model to account for regional economic shocks. Credit score is not used to segment the model because doing so would lead to certain risk segments becoming too sparse to produce reasonable projections. However, the share of accounts within three credit score categories (FICO® or equivalent “<= 620,” “> 620” and “N/A – Original credit score is missing or unknown”) is included as a variable in the model and used to project losses for bank and charge cards; credit score is a more informative risk signal than it is for business-use cards, as business-use credit cards tend to be less influenced by credit scores due to spending controls and broader financial capacity of businesses.

[632] “SME” is short for “small and medium sized enterprises.” In this context, “SME and Business cards” refer to small business credit cards.

[633] In addition to the above reasoning, bank cards and charge cards are combined as these categories are combined during the 2008 financial crisis period on the FR Y-14Q. These segments began to be reported separately after instruction changes to FR Y-14Q, Schedule A.3 (International Cards) took effect in 2012.

Alternative Macroeconomic and Other Variables

The Board considered various options for incorporating measures of the macroeconomic environment into the Other Retail models. The domestic models rely on the U.S. unemployment rate, as it serves as a key indicator of household economic conditions. This section describes alternatives to the method by which the U.S. unemployment rate is transformed prior to entering the models, and alternative variables that could be used to account for economic conditions.

Each of the domestic models uses the quarterly change in U.S. unemployment rate, sourced from the Bureau of Labor Statistics, as the proxy for macroeconomic conditions. The change in unemployment rate in general is more closely associated with increased default risk than the level of unemployment rate is.[634] This result is confirmed in the Board's data; for most portfolios, historical net charge-off rates are more closely correlated with changes in the unemployment rate, rather than levels of the unemployment rate. For the private student loan portfolio, the level of unemployment rate is an important predictor of net charge-off rate in addition to the quarterly change in the unemployment rate. The importance of the level of unemployment rate is specific to the Student Loan portfolio as the level of unemployment rate captures the job market conditions that directly impact the income prospects of new graduates with student loans. In contrast, the remaining Domestic portfolios generally involve borrowers with more stable income, so the level of unemployment rate is less relevant. The Board considered using the level of the unemployment rate for each of the models, but determined that the differences listed above—as well as the limited improvement in model fit when including the

[634] *See*, *e.g.*, Crook and Banasik (2012). Crook, J & Banasik, J, 2012, "Forecasting and explaining aggregate consumer credit delinquency behaviour", *International Journal of Forecasting*, 28(1), 145-60.

level of unemployment rate in these portfolios—justified adding the level of unemployment only to the Private Student Loan model specification.

Next, the Board considered the inclusion of different lags[635] of the quarterly change in unemployment rate in the models. Lags are justified for multiple reasons. First, both households and small businesses may have cash reserves that will allow them to avoid becoming delinquent or defaulting on loans immediately after job loss or declines in business. Second, it takes time after nonpayment begins for loans to become delinquent, default, and be charged off. In general, the Board relied on measures of model performance—such as R-squared and the statistical significance and interpretability of coefficients—to determine the number of lags to include in each equation. Including too many lags could complicate the model and risk capturing noise rather than underlying economic relationships, while including fewer lags may fail to capture the delayed effects and could prevent the model from accurately reflecting responses to economic conditions.

While the Domestic Models use the quarterly changes in the unemployment rate as the key macroeconomic specification, the Board also considered alternative transformations of the unemployment rate, including the year-over-year change in the unemployment rate (as opposed to the quarterly change used in the model) and the difference between the unemployment rate and the non-accelerating inflation rate of unemployment (NAIRU). However, using these variables either as standalone macroeconomic indicator or as additional terms did not improve the model's predictive accuracy. Moreover, the estimated coefficients on these variables when included are often not statistically significant or had signs opposite to those that would be expected by economic reasoning. These additional variables are therefore not included.

[635] A lag refers to the inclusion of past values of a variable (in this case, prior quarter's changes in the unemployment rate) to capture delayed effects.

The Board also considered including other economic variables in the models. For example, for the consumer portfolios (Other Consumer loan and Private Student loan), disposable personal income growth was also considered for inclusion. Conceptually, disposable personal income growth could meaningfully impact loss rates, as it reflects household financial conditions. However, over the sample period spanning from 2007 through the fourth quarter of 2019, disposable income growth generally moved similarly to unemployment rate changes, and when the two diverged, unemployment rate growth was more associated with increases in net charge-offs than disposable personal income growth. Including both terms does not meaningfully improve the model's predictive accuracy. For the Small Business loan and Small Business and Corporate Credit Card portfolios, the Board tested using financial variables including Chicago Board Options Exchange (CBOE) Market Volatility Index (VIX) and the corporate BBB bond yield in the regression. However, these terms did not substantially improve model performance. This indicates that loan performance of these portfolios is more closely tied to the real economy than the financial metrics, perhaps because small business borrowers depend on local demand and have limited access to capital markets. As a result, incorporating financial metrics did not significantly improve the model's ability to forecast net charge-off rates for these portfolios.

For the International Cards model, as previously described, the models include measures of both the local and global macroeconomic environment. Measures of local economic conditions are needed to account for changes in region-specific conditions, while measures of global conditions are necessary to reflect the interconnectedness of the global economy. The use of global economic conditions is observed frequently in the literature,[636] and using measures of

[636] *See*, *e.g.*, Rey (2018).

both global and local macroeconomic conditions is also seen in several studies.[637] To account for global economic conditions, the Board uses the U.S. unemployment rate. The U.S. GDP growth rate was also considered, as well as the Euro area unemployment rate and the Euro GDP growth rate; however, historic net charge-off rate more closely follows the path of the U.S. unemployment rate—even among borrowers whose current place of residency is outside of the U.S., which suggests that borrowers' income or financial obligations remain linked to the U.S. economy. Measures of local economic conditions were chosen to align the available data with the region-specific economy. Because, based on Board analysis comparing historical economic indicators of Canada and the United States such as real GDP growth and unemployment, the economies are closely correlated, the U.S. real GDP growth rate is used to measure regional economic conditions in Canada. Because the vast majority of loans in the EMEA and LATAM regions are in the Euro area and Mexico, respectively, the Euro area unemployment rate and Mexico GDP growth rate are used to measure regional economic conditions for each of these geographies, respectively. Finally, while the APAC region loans are more widespread geographically, the Developing Asia GDP rate keeps the model simple and provides a broader measure of regional economic conditions than any country-specific variables. These findings are bolstered by the regression results, which show that the model is reasonably sensitive to changes in the chosen regional economic indicators over time.

Finally, seasonality treatment was considered for all portfolios. Consumer financial health predictably changes throughout the year. Because the supervisory stress test exercise most commonly uses portfolio data as of December 31 of a given year, this could lead to higher or lower than reasonable loss estimates if the data exhibit seasonality. Empirical analyses by the

[637] *See*, *e.g.*, Xia and Zhou (2023).

Board—such as testing for seasonal effects in the regression specification and assessing seasonality based on the calculated coefficients—demonstrates that seasonality is not a meaningful concern for portfolios other than the student loan portfolio. This is further justified conceptually by the fact that many student loans start requiring payments shortly after graduation, which is concentrated during certain parts of the calendar year. Therefore, the private student loan models but not the other regression models include terms to account for seasonality ("quarter fixed effects").

(2) Scalar Models

Because the considerations for the Retail Non-Purpose Loan portfolio are different than that of the other portfolios, they are discussed separately.

International Scalar Models

In this section, "International Scalar Models" refer to the portfolios using scalar models, with the exception of the Retail Non-Purpose Loan portfolio, which is discussed separately.

One alternative approach to using scalar models for these portfolios is to rely on regression models instead. Regression models have the advantage of incorporating more granular information, allowing differentiation of projections across more dimensions. However, these advantages were insufficient to justify regression models for these portfolios. One key advantage of the scalar models is simplicity, as they sharply reduce implementation costs. Given the limited materiality in these portfolios, a simple approach is justified. Additionally, the limited historical data available in these portfolios makes them challenging to model using regression techniques; balances have also fallen further in recent years, adding additional complications.

In addition to the empirical challenges of modeling sparse portfolios, there are operational challenges as well. For instance, no firms currently report FR Y-14Q, Schedule A.8 (International Small Business), meaning contemporary segment-level data is not available. For portfolios that the Board models using regression techniques, the Board assigns the loss rate path of the 50th percentile firm to firms that report balances in a given portfolio on FR Y-14Q, Schedule M.1 (Balances), but whose balances are not sufficiently large to require reporting on the relevant schedule listed in Table G3 for that portfolio (see Section G.ii.a.(5) for more information). However, with no firm reporting FR Y-14Q, Schedule A.8 (International Small Business), no firm would receive a modeled loss rate that could be used to produce the 50th percentile path for other firms. A scalar model prevents this issue from creating operational challenges, by assigning a single loss rate path for all firms in the portfolio.

A second alternative is to use a scalar approach, but rather than calibrate this scalar off of the reported industry data, one would instead reweight the industry loss rates based on the segment distribution in a more recent period. For instance, if a portfolio shifted from a higher share of balances in the low credit score (<=620 FICO® or equivalent) to a lower share, the calculation could reweight the segments such that the early periods align with the segmentation in more recent periods. As many portfolios have become less risky in terms of observable characteristics since the 2008 financial crisis period, reweighting would generally have the effect of reducing loss projections. While this approach has benefits, it is ultimately not applied. Compared to the reweighting approach, the chosen scalar model is simpler to calculate. Furthermore, because portfolios are dynamic over time, the scalars would have to be recalibrated frequently to stay in alignment with the current portfolio, adding additional complexity. Finally, similar to the regression model, the limited information on current portfolios—including portfolios where no firm is reporting the relevant data schedule on the FR Y-14Q—prevents the Board from identifying current segmentation. Therefore, based on concerns regarding limited materiality, simplicity, and operational burden, the Board uses the scalar models as described above to project losses in these portfolios.

Retail Non-Purpose Loans

The Retail Non-Purpose loan portfolio uses a scalar loss rate equivalent to that projected by the wholesale model for loans for purchasing and carrying securities. Unlike the rest of the Other Retail portfolios, no segment-level data on the Retail Non-Purpose loan portfolio is available, either to fit a regression model or to project net charge-off rates based on this regression model. The limited loss information available[638] on regulatory reporting forms suggests that the loss rates in this portfolio are very small, reflecting the liquid collateral and strong risk-management practices associated with loans collateralized by securities. Based on these factors, the scalar loss rate is applied, despite the substantial balances reported in this portfolio.

To recalibrate the stress loss rate for this portfolio, or to use a more complex modeling framework, additional data collection would be required.

iii. Key Assumptions for the Other Retail Model

a. *Estimation Sample Period*

Each of the Other Retail models, to the extent data are available, relies on a sample period beginning in the first quarter of 2007 and ending in the fourth quarter of 2019. The beginning of the period corresponds to the beginning of the period for which FR Y-14Q data are

[638] Although a limited number of firms have reported losses on this loan since 2017 on Item 33 of the FR Y-14A, Schedule A.1.a - Income Statement, data on how the loan performs under severe economic conditions such as the 2008 financial crisis remains unavailable, and the reported losses have been negligible.

available. The end of the period corresponds to the last period before the beginning of the COVID-19 pandemic, during which historic relationships between macroeconomic variables and the net charge-off rate broke down. Most notably, the unemployment rate sharply increased in 2020, while net charge-off rates remained stable, as a result of government support programs that allowed household financial conditions to remain strong despite high unemployment. These relationships likely reflect the unique circumstances of the COVID shock, and will likely not be reflective of future behavior.

Academic research corroborates the view that the economic distortions in 2020 and the years following are significant, and that the observed relationships between the economic environment and borrower behavior during this period are unique to it. For example, Stock and Watson (2025) find that the COVID shock was notable, but had “largely disappeared by late 2022.”[639] This finding raises concerns that if data covering 2020-2022 are used to estimate the model coefficients, these coefficients may be impacted by the distortions that caused these unusual observed relationships.

As a result, to properly incorporate more recent data into the estimation datasets, it would be necessary to account for this period. Possible treatments include adding a “pandemic treatment” indicator variable to the specifications, adding additional macroeconomic variables to the specification, or removing the impacted periods entirely. In the future, the Board may choose to incorporate additional periods into the estimation sample; however, the current sample period is still sufficient to produce reasonable loss projections.

[639] Stock, J. and M. Watson (2025). “Recovering from COVID., NBER working paper 33857.

b. Concerns Over Unit Root (Applicable to the Regression Models Only)

The Other Retail regression models rely on previous values of net charge-off rates (and in the case of the International Cards Model, delinquency rates) to project values of these variables in a given period. As described in Section G.ii.b.(1), models that rely on previous values of the outcome variables are referred to as "autoregressive." Generally with autoregressive specifications, there are technical concerns that they may not be mean-reverting, meaning the model's behavior might not necessarily return to a long-term average after a shock. The Board conducted statistical testing and model performance testing to ensure that the estimated Other Retail regression models have reasonable macro-sensitivity and do not produce so-called "straight-line" net charge-off projections that certain non-mean-reverting models, such as models with unit roots, are known to produce.

c. Constant Macro-Sensitivity Across Segments (Applicable to Regression Models Only)

The structure of the Domestic Models imposes that all segments within a portfolio, and therefore, all loans within the portfolio, share common sensitivity to macroeconomic conditions. In practice, this leads to over-prediction in the less risky segments, and under-prediction in the riskier segments, as net charge-off rates historically increase more in risky segments during periods of economic stress compared to less risky segments.

This assumption could be relaxed by allowing an interaction between risk segments and the macroeconomic variables in the model; however, doing so would lead to challenges of its own. First, not all interaction terms in the portfolio would be significant, and including these terms could increase model complexity. As a result, the model may perform well on past data but struggle to give accurate forward-looking predictions, and may become less stable. Moreover, given the limited number of observations used to fit the models, there is risk that adding an additional interaction term would reduce the power of the model because of the small sample size. The Board therefore continues to apply this constant macro-sensitivity assumption.

In the International Cards model, there are two levels of common variable sensitivity. First, the model does not separately estimate the sensitivity of the outcome variables to certain independent variables by credit card type; instead, it assumes a common response across all loans. This process applies to all of the macroeconomic variables, as well as the previous quarter's net charge-off rate, in the net charge-off rate equation, and the previous quarter's delinquency rate, in both the net charge-off rate and delinquency rate equations. This is a reasonable approach because only a few firms report these portfolios, which makes it difficult to estimate product-specific effects. To address data limitations, the Board uses a single model to project losses for both International Bank Card and Charge Cards and International Small Business and Corporate Credit Cards. This helps mitigate the issue of sparse data by allowing historical International Bank and Charge Card behavior to inform projections of the smaller International Small Business and Corporate Card portfolio; however, a trade-off is that combining the portfolios into a single model implicitly assumes that the sensitivity of each portfolio to many variables is the same. Second, the model assumes that a single global macroeconomic factor impacts most or all geographic regions equally.[640] This is reasonable given that the sample period from 2007 to 2019 includes only one major global downturn that affects most regions—the 2008 global financial crisis, which originated in the United States. However, model performance may be less reliable under a hypothetical scenario with a localized downturn that primarily affects a specific region but has little or no impact on the U.S. economy.

[640] *See* Section G.ii.b.(1) for a detailed explanation.

iv. Questions

Question G1: The Board seeks comment on the treatment of student loan balances that are not in repayment. Should the Student Loan model continue to apply zero losses to balances that are not in repayment (due to being in a grace period, deferment, or in forbearance)? If a loss rate of greater than zero is preferable, how should it be calibrated to account for repayment status?

Question G2: The Board seeks comment on whether to collect additional data covering the current and historical balances, risk characteristics, and losses of Retail Non-Purpose loans to facilitate the development of a more robust model.

Question G3: The Board seeks comment on whether to implement a model that allows the sensitivity of net charge-off rate to the macroeconomic environment to vary by risk segment, rather than assuming that macro-sensitivity is constant across segments.